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TABLE 2. List of abbreviations

IDS	Intrusion Detection System	**MI**	Mutual Information
NIDS	Network-based Intrusion Detection System	**LSTM**	Long Short Term Memory
HIDS	Host-based Intrusion Detection System	**TF-IDF**	Term Frequencies and Inverse Document Frequencies
ML	Machine Learning	**NN**	Neural Network
DL	Deep Learning	**GRU**	Gated Recurrent Unit
BoW	Bag-of-Word	**MLP**	Multilayer Perceptron
DLL	Dynamic Link Library	**F1**	F1-score
ACC	Accuracy	**TP**	True Positive
DT	Decision Tree	**FN**	False Negative
SVM	Support Vector Machine	**PRC**	Precision
NB	Naive Bayes	**REC**	Recall
CNN	Convolutional Neural Network	**FPR**	False Positive Rate
LR	Logistic Regression	**RNN**	Recurrent Neural Networks
RF	Random Forest	**IoT**	Internet of Things
XGBoost	Extreme Gradient Boosting	**AdaBoost**	Adaptive Boosting

A. ADFA-LD

The ADFA-LD dataset contains system call sequences varying in length from the Linux operating system. Each system call sequence consists of unique IDs representing system calls. Figure 1 shows an example of a system call sequence from this dataset. ADFA-LD is divided into three subsets: training, validation, and attack. The training and validation subsets contain normal-type system call sequences. The attack subset includes system call sequences related to six different attack types. The numbers of system call sequences and attack types in ADFA-LD are given in Table 3.

TABLE 3. Numbers of system call sequences and attack types in ADFA-LD

Training	Validation	Attack	Total
833	4372	Add Superuser: 91 FTP password bruteforce: 162 SSH password Bruteforce: 176 Java Meterpreter: 124 Linux Meterpreter: 75 Web shell attack: 118 Total: 746	5951

The number of normal-type system call sequences in ADFA-LD is approximately seven times greater than that of attack-type sequences. Thus, it is concluded that there is an imbalance in this dataset. Considering this, this study aims to use a balanced dataset containing system call sequences from ADFA-LD. To this end, the training and attack subsets of the ADFA-LD dataset are combined. Consequently, a balanced dataset is created, consisting of 833 normal and 746 attack system call sequences, totaling 1579 sequences. This balanced dataset is used in the development and evaluation phases of the models.

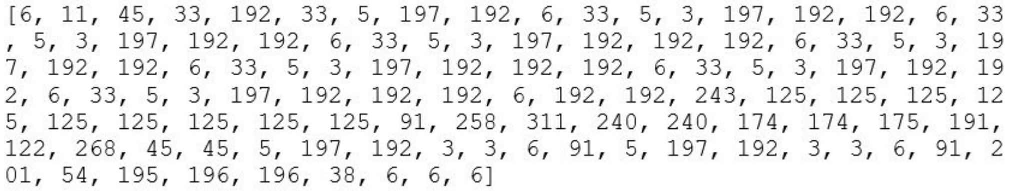
B. ADFA-WD

The ADFA-WD dataset consists of DLL call sequences from the Windows XP operating system. Each DLL call sequence is represented by DLL calls identified by DLL names and specific memory access addresses. An example of a DLL call sequence from this dataset is shown in Figure 2. ADFA-WD includes three subsets: training, validation, and attack. The training and validation subsets contain normal-type DLL call sequences, with 355 and 1827 sequences, respectively. The attack dataset includes 5542 DLL call sequences covering 12 different attack types. The numbers of DLL call sequences and attack types in ADFA-WD are given in Table 4.

TABLE 4. Numbers of system call sequences and attack types in ADFA-WD

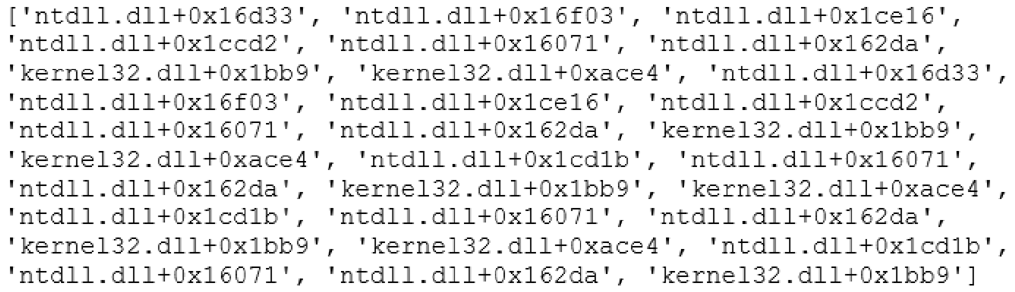
Training	Validation	Attack	Total
355	1827	V1-CesarFTP : 454 V2-WebDAV : 470 V3-Icecast : 382 V4-Tomcat : 418 V5-OS-SMB: 355 V6-OS-Print-Spool: 454 V7-PMWiki: 430 V8-Wireless-Karma: 487 V9-PDF: 440 V10-Backdoored Executable: 536 V11-Browser-Attack: 495 V12-Infectious-Media: 621 Total: 5542	7724

The number of attack-type DLL call sequences in ADFA-WD is approximately 2.5 times greater than that of normal-type sequences. Thus, there is an imbalance problem in this dataset. In response to this issue, this study aims to use a balanced dataset consisting of DLL call sequences from ADFA-WD. To achieve this goal, the training and validation subsets of the dataset are combined. As a result, 2182 normal-type DLL call sequences are gathered. The attack-type DLL call sequences are selected to balance with the number of normal-type sequences. In the selection process, 40% of the DLL call sequences in the attack subset are randomly chosen.



```
[6, 11, 45, 33, 192, 33, 5, 197, 192, 6, 33, 5, 3, 197, 192, 192, 6, 33
, 5, 3, 197, 192, 192, 6, 33, 5, 3, 197, 192, 192, 192, 6, 33, 5, 3, 19
7, 192, 192, 6, 33, 5, 3, 197, 192, 192, 192, 6, 33, 5, 3, 197, 192, 19
2, 6, 33, 5, 3, 197, 192, 192, 192, 6, 192, 192, 243, 125, 125, 125, 12
5, 125, 125, 125, 125, 125, 91, 258, 311, 240, 240, 174, 174, 175, 191,
122, 268, 45, 45, 5, 197, 192, 3, 3, 6, 91, 5, 197, 192, 3, 3, 6, 91, 2
01, 54, 195, 196, 196, 38, 6, 6, 6]
```

FIGURE 1. A system call sequence in the ADFA-LD dataset



```
['ntdll.dll+0x16d33', 'ntdll.dll+0x16f03', 'ntdll.dll+0x1ce16',
'ntdll.dll+0x1ccd2', 'ntdll.dll+0x16071', 'ntdll.dll+0x162da',
'kernel32.dll+0x1bb9', 'kernel32.dll+0xace4', 'ntdll.dll+0x16d33',
'ntdll.dll+0x16f03', 'ntdll.dll+0x1ce16', 'ntdll.dll+0x1ccd2',
'ntdll.dll+0x16071', 'ntdll.dll+0x162da', 'kernel32.dll+0x1bb9',
'kernel32.dll+0xace4', 'ntdll.dll+0x1cd1b', 'ntdll.dll+0x16071',
'ntdll.dll+0x162da', 'kernel32.dll+0x1bb9', 'kernel32.dll+0xace4',
'ntdll.dll+0x1cd1b', 'ntdll.dll+0x16071', 'ntdll.dll+0x162da',
'kernel32.dll+0x1bb9', 'kernel32.dll+0xace4', 'ntdll.dll+0x1cd1b',
'ntdll.dll+0x16071', 'ntdll.dll+0x162da', 'kernel32.dll+0x1bb9']
```

FIGURE 2. A DLL call sequence in the ADFA-WD dataset

Thus, 2217 attack-type DLL call sequences are obtained. Consequently, a balanced dataset consists of 2182 normal and 2217 attack-type DLL call sequences, totaling 4399. This balanced dataset is used to develop models and measure their performance.

III. Preprocessing and Feature Selection

In this section, the application of n-gram and BoW methods on the ADFA-LD and ADFA-WD datasets, as well as the process of creating BoW datasets, is discussed. Additionally, the procedure for reducing the dimensions of the created BoW datasets and selecting optimal features is explained.

A. Application of N-Gram Method

To capture the relationships and transitions between system/DLL calls, n-grams of various lengths are generated from raw call sequences. In finding n-grams within call sequences, a window size is determined based on the value of n. Subsequently, the window is positioned to encompass the first system/DLL call in the sequence, identifying the first n-gram. To identify subsequent n-grams, the window is shifted to the right, with each shift starting from the next system/DLL call. This process continues until the window reaches the last system/DLL call in the sequence, thereby identifying all n-grams within the call sequence.

For example, Figure 3 illustrates the process of identifying n-grams for two system call sequences of varying lengths, similar to those found in ADFA-LD. Figure 4 displays a small portion of the n-grams and their counts obtained after applying the n-gram identification process to system call sequences in ADFA-LD. Additionally, Figure 5 presents the n-grams obtained after applying the process outlined in Figure 3 to three DLL call sequences of different lengths, similar to those in ADFA-WD.

In the operation conducted on the ADFA datasets with an n value of 5, 80,526 unique 5-grams are obtained from the system call sequences in ADFA-LD. Similarly, 40,752 unique 5-grams are identified from the 4,399 DLL call sequences in ADFA-WD.

After identifying the 5-grams from the call sequences in the datasets, each 5-gram is assigned a numerical label. For example, ”N-gram_1” represents the first 5-gram. Following the labeling process, 5-gram datasets are created, where each 5-gram is treated as a feature. In these 5-gram datasets, the value of each 5-gram for a particular call sequence corresponds to its frequency within that sequence. As a result, two 5-gram datasets corresponding to the ADFA datasets are obtained. An example of a 5-gram dataset, constructed from the n-grams shown in Figure 3, is presented in Figure 6.

B. Application of BoW Methods

Standard BoW, binary BoW, probability BoW, and TF-IDF BoW methods, which are frequently used in the fields of text mining and natural language processing, are applied to the 5-gram datasets derived from the ADFA datasets. During the application process, the new values of the 5-grams, which are the features of the datasets, are calculated by the BoW methods. As a result of the application, BoW datasets corresponding to each BoW method are created. These BoW datasets are used in ML models' training and testing phases.

1) Standart BoW

The standard BoW method calculates the frequency of words within text datasets. Initially, it identifies the unique words in the texts. Each unique word is considered a feature. The values of these features correspond to the frequency of the

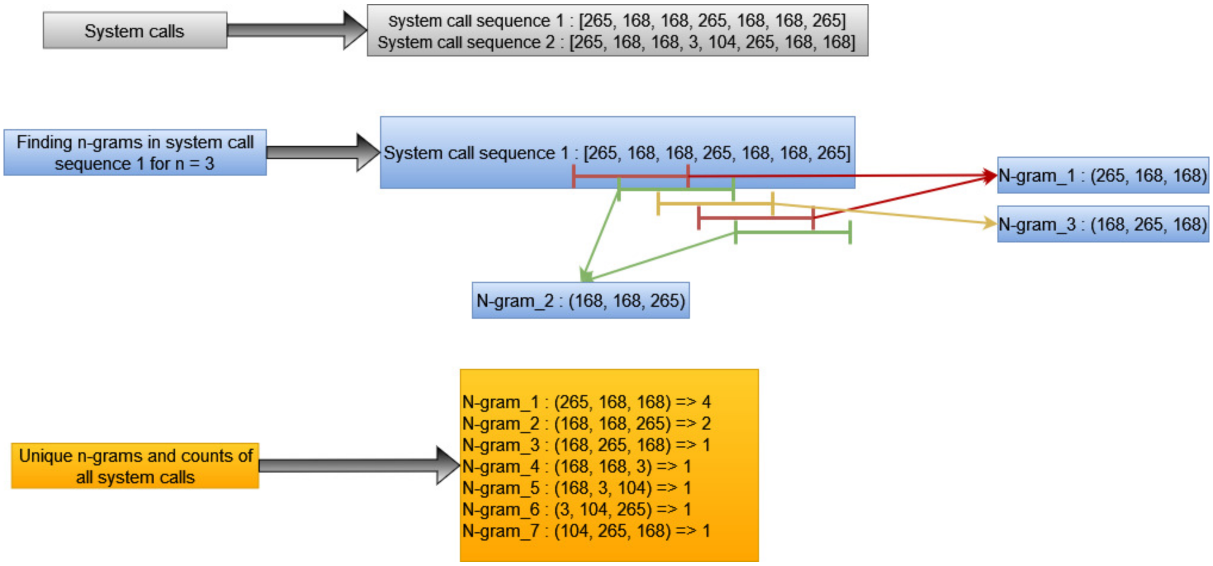
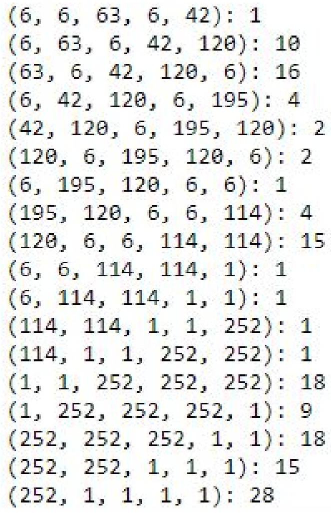

System calls
System call sequence 1 : [265, 168, 168, 265, 168, 168, 265]
System call sequence 2 : [265, 168, 168, 3, 104, 265, 168, 168]
Finding n-grams in system call sequence 1 for n = 3
System call sequence 1 : [265, 168, 168, 265, 168, 168, 265]
N-gram_1 : (265, 168, 168)
N-gram_3 : (168, 265, 168)
N-gram_2 : (168, 168, 265)
Unique n-grams and counts of all system calls
N-gram_1 : (265, 168, 168) => 4
N-gram_2 : (168, 168, 265) => 2
N-gram_3 : (168, 265, 168) => 1
N-gram_4 : (168, 168, 3) => 1
N-gram_5 : (168, 3, 104) => 1
N-gram_6 : (3, 104, 265) => 1
N-gram_7 : (104, 265, 168) => 1

FIGURE 3. The process of finding unique n-grams of call sequences



```
(6, 6, 63, 6, 42): 1
(6, 63, 6, 42, 120): 10
(63, 6, 42, 120, 6): 16
(6, 42, 120, 6, 195): 4
(42, 120, 6, 195, 120): 2
(120, 6, 195, 120, 6): 2
(6, 195, 120, 6, 6): 1
(195, 120, 6, 6, 114): 4
(120, 6, 6, 114, 114): 15
(6, 6, 114, 114, 1): 1
(6, 114, 114, 1, 1): 1
(114, 114, 1, 1, 252): 1
(114, 1, 1, 252, 252): 1
(1, 1, 252, 252, 252): 18
(1, 252, 252, 252, 1): 9
(252, 252, 252, 1, 1): 18
(252, 252, 1, 1, 1): 15
(252, 1, 1, 1, 1): 28
```

FIGURE 4. A small part of unique n-grams and their counts of system call sequences in ADFA-LD

words within the text. Thus, texts are represented by the unique words they contain and the frequency values of those words.

When the standard BoW method is applied to 5-gram datasets, each 5-gram is treated as a word. The value of each 5-gram is calculated similarly to the frequency of unique words within a text. In the 5-gram datasets, the repetition counts of 5-grams within the call sequences are recorded. These repetition counts represent the frequency values of the 5-grams within the call sequences. Therefore, the 5-gram datasets serve as the standard BoW method applied to them. In other words, the 5-gram datasets derived from the ADFA datasets are identical to the standard BoW datasets.

2) Binary BoW

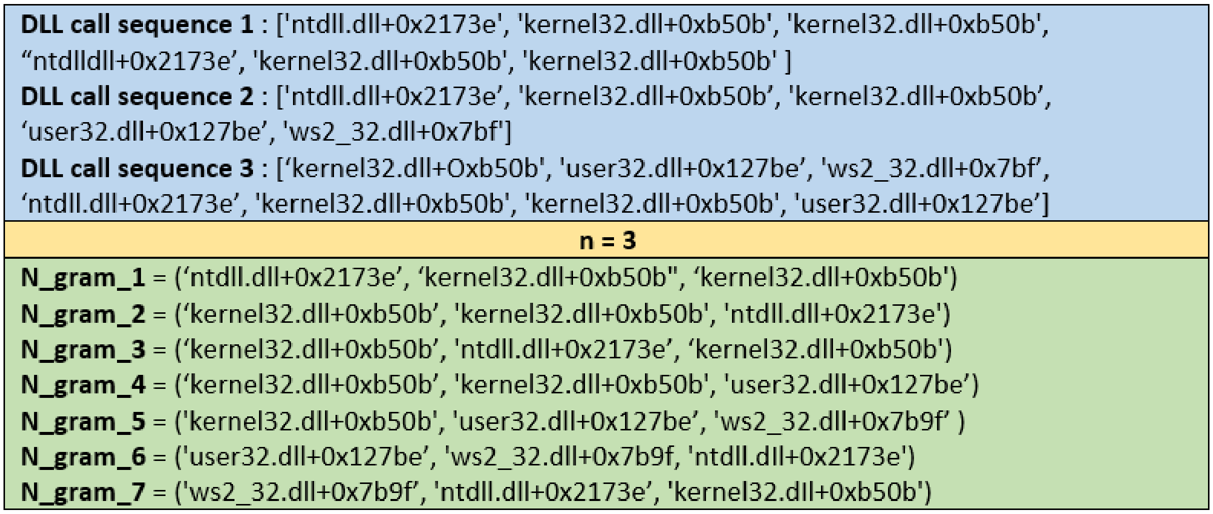
The binary BoW method focuses on whether words are present in the texts within a text dataset rather than calculating the frequency of the words. If a word, considered a feature representing a text, is found in the text, its value is set to 1. Otherwise, its value is set to 0. As a result, texts are represented by 0s and 1s corresponding to the presence or absence of words.

When the binary BoW method is applied to 5-gram datasets, the values of each 5-gram, which are treated as words, are examined. If the value of a 5-gram in a system/DLL call is greater than 0, its new value is set to 1. Conversely, if the 5-gram value is 0, it remains 0. As a result, two binary BoW datasets are created, where the 5-gram values are either 0 or 1. An example of a binary BoW dataset, obtained by applying the binary BoW method to the n-gram dataset shown in Figure 6, is illustrated in Figure 7.

3) Probability BoW

The probability BoW method calculates the likelihood of words appearing in texts. The probability value of a word is determined by dividing the frequency of the word in the text by the sum of the frequencies of all words. Thus, the texts are represented by the probability values of the words used as features.

When the probability BoW method is applied to 5-gram datasets, the probability values of the 5-grams, which are treated as words, are calculated using Equation 1. In this equation, the probability value of any 5-gram in a call sequence is determined by dividing the value of the respective 5-gram by the total value of all n-grams. After calculating the probability values of the 5-grams for each system/DLL call sequence, two probability BoW datasets containing the probability values of the 5-grams from the ADFA datasets

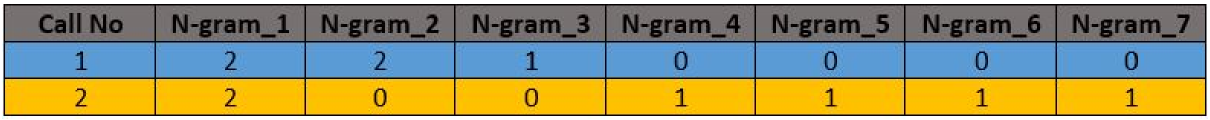


DLL call sequence 1 : ['ntdll.dll+0x2173e', 'kernel32.dll+0xb50b', 'kernel32.dll+0xb50b', “ntdlldll+0x2173e’, 'kernel32.dll+0xb50b', 'kernel32.dll+0xb50b']
DLL call sequence 2 : ['ntdll.dll+0x2173e’, 'kernel32.dll+0xb50b’, 'kernel32.dll+0xb50b’, ‘user32.dll+0x127be’, 'ws2_32.dll+0x7bf']
DLL call sequence 3 : [‘kernel32.dll+Oxb50b', 'user32.dll+0x127be’, 'ws2_32.dll+0x7bf’, ‘ntdll.dll+0x2173e’, 'kernel32.dll+0xb50b', 'kernel32.dll+0xb50b', 'user32.dll+0x127be’]

n = 3

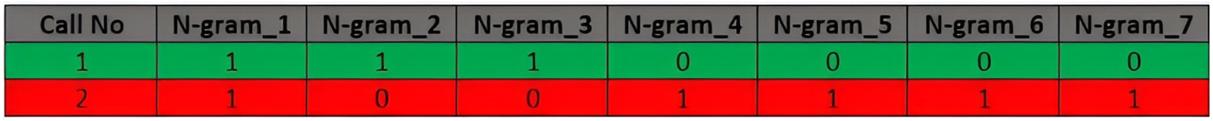
N_gram_1 = (‘ntdll.dll+0x2173e’, ‘kernel32.dll+0xb50b", ‘kernel32.dll+0xb50b')
N_gram_2 = (‘kernel32.dll+0xb50b’, 'kernel32.dll+0xb50b', 'ntdll.dll+0x2173e')
N_gram_3 = (‘kernel32.dll+0xb50b’, 'ntdll.dll+0x2173e’, ‘kernel32.dll+0xb50b')
N_gram_4 = (‘kernel32.dll+0xb50b’, 'kernel32.dll+0xb50b', 'user32.dll+0x127be’)
N_gram_5 = ('kernel32.dll+0xb50b', 'user32.dll+0x127be’, 'ws2_32.dll+0x7b9f’)
N_gram_6 = ('user32.dll+0x127be’, 'ws2_32.dll+0x7b9f, 'ntdll.dll+0x2173e')
N_gram_7 = ('ws2_32.dll+0x7b9f’, 'ntdll.dll+0x2173e’, 'kernel32.dll+0xb50b')

FIGURE 5. Unique n-grams of call sequences similar to DLL call sequences in ADFA-WD



Call No	N-gram_1	N-gram_2	N-gram_3	N-gram_4	N-gram_5	N-gram_6	N-gram_7
1	2	2	1	0	0	0	0
2	2	0	0	1	1	1	1

FIGURE 6. An example n-gram dataset



Call No	N-gram_1	N-gram_2	N-gram_3	N-gram_4	N-gram_5	N-gram_6	N-gram_7
1	1	1	1	0	0	0	0
2	1	0	0	1	1	1	1

FIGURE 7. An example binary BoW dataset

are obtained. Figure 8 presents an example of a probability BoW dataset created by applying the probability BoW method to the n-gram dataset shown in Figure 6.

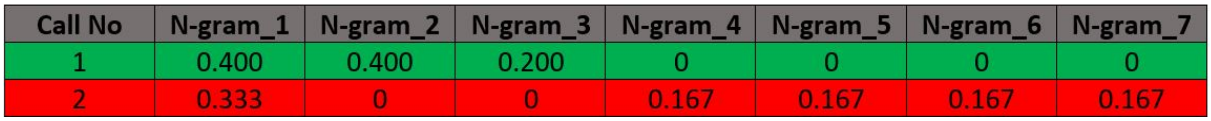
$$P(5-gram_i) = \frac{\text{The value of } 5-gram_i \text{ in a sequence}}{\text{Total value of } 5-grams \text{ in a sequence}} \tag{1}$$

4) TF-IDF BoW

The TF-IDF BoW method is used to determine the importance of a word within a document. The importance of a word is based on its frequency within the document and its prevalence across all documents. The method first identifies the unique words within the documents and calculates their term frequency (TF) values. Typically, the TF value of a word is its frequency within the document. The words' inverse document frequency (IDF) values measure their prevalence across all documents. The IDF value of a word is calculated by dividing the total number of documents by the number of documents containing the word and then taking the logarithm of this ratio (base 10). The product of the TF and IDF values provides the TF-IDF values of the words. Thus, documents are represented by the TF-IDF values of their unique words, each considered a feature.

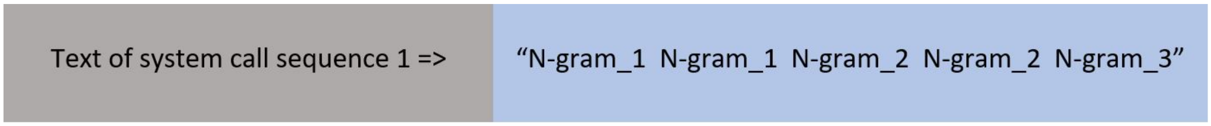
Before applying the TF-IDF BoW method to the 5-gram datasets, the sequences represented by 5-grams are converted into text format. During this conversion, the labels of the 5-grams with non-zero values are used. The labels of these 5-grams are concatenated with spaces in between, according to the values of the 5-grams. Thus, each sequence is transformed into a text composed of the labels of the 5-grams. For example, the text representation of the first system call sequence from the n-gram dataset shown in Figure 6 can be found in Figure 9.

After converting each sequence in the 5-gram datasets into text format, the texts are processed using the TF-IDF BoW method. The TF-IDF values of the words (5-grams) in the texts are calculated using the TfidfVectorizer method from the scikit-learn library. The default parameters of the TfidfVectorizer method are used during this calculation. As a result, two TF-IDF BoW datasets are obtained, where the features are the TF-IDF values of the 5-grams, and these features represent the sequences. For example, the TF-IDF BoW dataset obtained from the n-gram dataset shown in Figure 6 is illustrated in Figure 10.



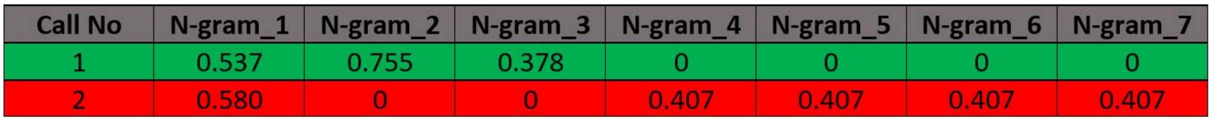
Call No	N-gram_1	N-gram_2	N-gram_3	N-gram_4	N-gram_5	N-gram_6	N-gram_7
1	0.400	0.400	0.200	0	0	0	0
2	0.333	0	0	0.167	0.167	0.167	0.167

FIGURE 8. **An example probability BoW dataset**



Text of system call sequence 1 => “N-gram_1 N-gram_1 N-gram_2 N-gram_2 N-gram_3”

FIGURE 9. **Text of a sample system call sequence**



Call No	N-gram_1	N-gram_2	N-gram_3	N-gram_4	N-gram_5	N-gram_6	N-gram_7
1	0.537	0.755	0.378	0	0	0	0
2	0.580	0	0	0.407	0.407	0.407	0.407

FIGURE 10. **An example TF-IDF BoW dataset**

C. Feature Selection

To reduce detection and classification times in models using BoW datasets, it is necessary to reduce the dimensionality of these datasets and select optimal features. The steps outlined in Algorithm 1 are applied to the BoW datasets to achieve this. In this algorithm, the MI method and the k-means clustering algorithm are used together.

According to Algorithm 1, the first step involves calculating the MI values of the features in the datasets. Subsequently, features are clustered into two groups based on their MI values using the k-means algorithm. One group contains features with low MI values, while the other comprises features with high MI values. Only the features from the cluster with high MI values are utilized during model development and evaluation. The statistical information regarding the features obtained and used after the feature selection process is provided in Tables 5 and 6.

Algorithm 1 Feature selection algorithm

```
Input: BoW dataset
Output: BoW dataset with selected features and reduced dimensionality
k = 2                                        ▷ k is the cluster number
Calculating MI values of features
k-means(k, MI values along with the indexes of the features)
Selecting features in the set containing large MI values according to their indexes
return BoW dataset with selected features and reduced dimensionality
```

IV. Development and Evaluation of Proposed Stacking Ensemble Based HIDSs

In analyzing the ADFA datasets, n-grams are extracted using an n value of 5, creating 5-gram datasets where these n-grams are considered features. These datasets are then processed using various BoW methods, each producing distinct BoW datasets. Next, feature selection is performed on the BoW datasets according to Algorithm 1. The selected features are then used to develop and evaluate the models.

For model training, 75% of the data from the BoW datasets is utilized, while the remaining 25% is used for performance evaluation. The process of developing models using BoW datasets derived from 5-gram datasets is summarized in Figure 11. Individual models are developed, including KNN, DT, LR, and RF. Following this, ensemble models such as XGBoost and AdaBoost, which combine the outputs of the individual models, are created, resulting in stacking ensemble models. As a result, stacking ensemble based HIDSs are being developed.

Additionally, the models in this study are developed using the Google Colaboratory environment with Python programming, utilizing the scikit-learn, LightGBM, and NumPy libraries.

A. Evaluation Metrics

The performance of the models developed using BoW datasets is evaluated based on several metrics, including precision (PRC), recall (REC), f1-score (F1), FPR, ACC, training time, and testing time. To calculate PRC, REC, F1, FPR, and ACC metrics, the values of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) are required. The definitions of TP, TN, FP, and FN are listed below:

- ***TP:*** The number of positive samples correctly classified as positive.
- ***TN:*** The number of negative samples correctly classified as negative.
- ***FP:*** The number of negative samples incorrectly classified as positive.

TABLE 5. Number of selected features after applying feature selection process on BoW datasets derived ADFA-LD

	Standard BoW Dataset	Binary BoW Dataset	Probability BoW Dataset	TF-IDF BoW Dataset
Raw Feature Count	80526	80526	80526	80526
Selected Feature Count	18722	18508	18634	18338

TABLE 6. Number of selected features after applying feature selection process on BoW datasets derived ADFA-WD

	Standard BoW Dataset	Binary BoW Dataset	Probability BoW Dataset	TF-IDF BoW Dataset
Raw Feature Count	40752	40752	40752	40752
Selected Feature Count	5887	589	462	461

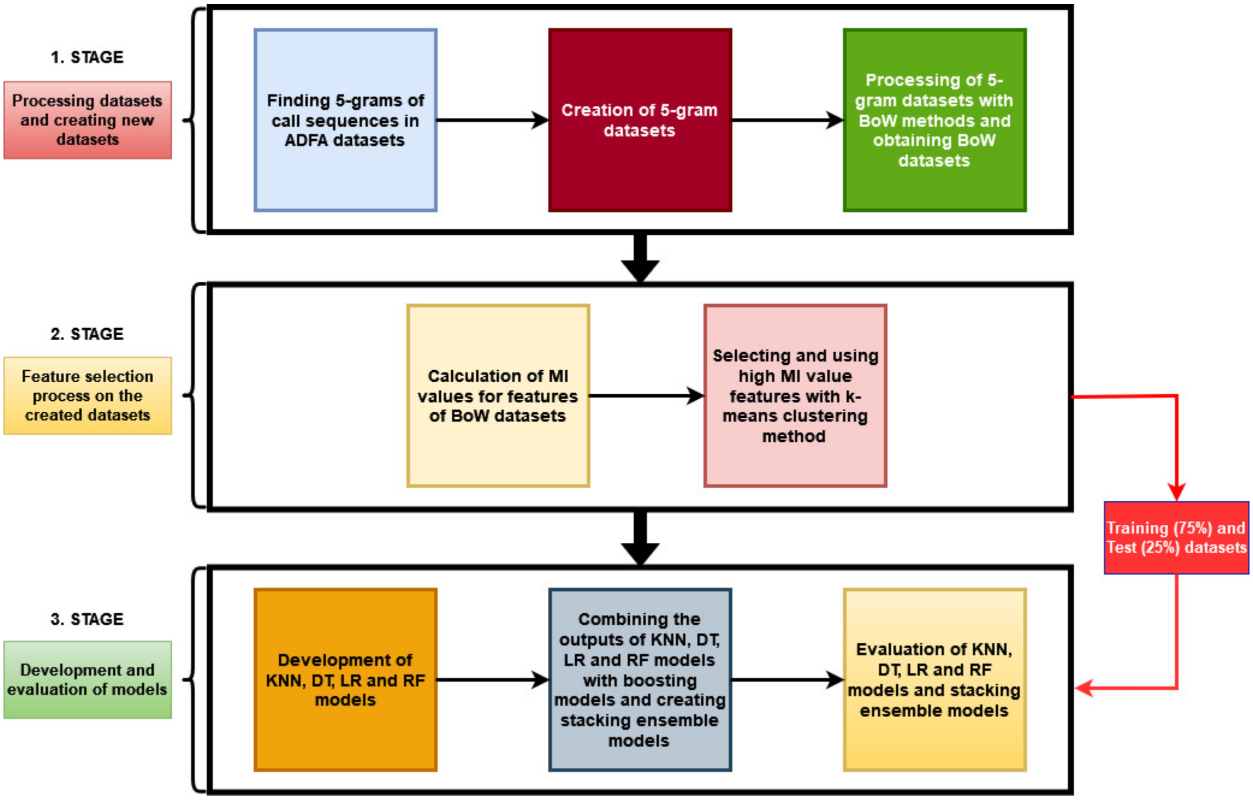

1. STAGE
Processing datasets and creating new datasets
Finding 5-grams of call sequences in ADFA datasets
Creation of 5-gram datasets
Processing of 5-gram datasets with BoW methods and obtaining BoW datasets
2. STAGE
Feature selection process on the created datasets
Calculation of MI values for features of BoW datasets
Selecting and using high MI value features with k-means clustering method
Training (75%) and Test (25%) datasets
3. STAGE
Development and evaluation of models
Development of KNN, DT, LR and RF models
Combining the outputs of KNN, DT, LR and RF models with boosting models and creating stacking ensemble models
Evaluation of KNN, DT, LR and RF models and stacking ensemble models

FIGURE 11. Development process of stacking ensemble models based on ADFA datasets

- ***FN:*** The number of positive samples incorrectly classified as negative.

The descriptions and mathematical equations for the metrics PRC, REC, F1, FPR, ACC, training time, and testing time are provided below.

- ***PRC:*** The ratio of the number of correctly classified positive samples to the total number of samples classified as positive.

$$PRC = \frac{TP}{TP + FP} \tag{2}$$

- ***REC:*** The ratio of the number of correctly classified positive samples to the total number of actual positive samples.

$$REC = \frac{TP}{TP + FN} \tag{3}$$

- ***F1:*** The harmonic mean of the PRC and REC values.

$$F1 = 2 * \frac{PRC * REC}{PRC + REC} \tag{4}$$

- ***FPR:*** The ratio of misclassified negative samples to total negative samples.

$$FPR = \frac{FP}{FP + TN} \tag{5}$$

- ***ACC:*** The ratio of correctly classified samples to the total number of samples.

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

- ***Training Time:*** The total time elapsed during the training of a model.
- ***Testing Time:*** The total time elapsed for a model to classify all test samples.

B. Evaluation of ADFA-LD Based Models

Tables 7 and 8 present the performance values of models using all features or selected features from ADFA-LD based BoW datasets in detecting attacks and anomaly events and in binary classification. When the models that use all the features are evaluated,

- Regarding the ACC metric, the most successful was the ensemble model XGBoost, which achieved an ACC of 0.9722. This performance value was obtained on both the standard BoW and probability BoW datasets.
- In terms of the FPR metric, the most successful model was the ensemble model AdaBoost, which achieved an FPR of 0.0236. This performance value was attained on the TF-IDF BoW dataset.
- Regarding the testing time metric, the most successful model was the DT model, which achieved a time of 0.0490 seconds. This time was obtained on the binary BoW dataset.

When examining the models developed with the selected features from the ADFA-LD based BoW datasets,

- In terms of the ACC metric, the most successful model was the XGBoost ensemble model, with an ACC of 0.9747. This performance value was achieved on the standard BoW dataset.
- Regarding the FPR metric, the most successful were the ensemble models XGBoost and AdaBoost, which both achieved an FPR of 0.0283. The XGBoost model reached this performance value on the probability BoW dataset. Meanwhile, the AdaBoost model achieved the best FPR values on both the standard BoW and probability BoW datasets.
- In terms of the testing time metric, the most successful model was LR, achieving a time of 0.0139 seconds. The LR model obtained this duration on the TF-IDF BoW dataset.

When comparing models developed using all or selected features from ADFA-LD based BoW datasets,

- In experiments conducted on the standard BoW dataset, models using all features generally exhibited better performance values regarding ACC and FPR metrics than their counterparts using selected features. The model that achieved the highest performance in terms of ACC was the XGBoost model with selected features. On the other hand, the best FPR values were reached by the XGBoost model with all features and the AdaBoost models with all or selected features.
- In experiments performed on the binary BoW dataset, models using selected features generally performed better regarding ACC and FPR metrics than their counterparts using all features. The XGBoost model with selected features achieved the highest ACC value. At the same time, the best performance in terms of FPR was demonstrated by the AdaBoost model with selected features.
- In experiments completed on the probability BoW dataset, models using selected features generally achieved better ACC and FPR metrics results than their counterparts using all features. The most successful model in terms of ACC was XGBoost, whether it used all or selected features. On the other hand, the best value for the FPR metric was achieved by the XGBoost models with either all or selected features, the AdaBoost model with selected features, and the LR model with all features.
- In experiments conducted on the TF-IDF BoW dataset, models using selected features generally performed better in terms of ACC and worse in terms of FPR compared to their counterparts using all features. The highest ACC values were achieved by the XGBoost model using either all or selected features and the AdaBoost model with selected features. In addition, the best FPR value was obtained by the AdaBoost model using all features.
- In all ADFA-LD based BoW datasets, models using selected features exhibited significantly better testing time values than their counterparts using all features.

C. Evaluation of ADFA-WD Based Models

Tables 9 and 10 contain the experimental results of models that use either all features or selected features from the ADFA-WD based BoW datasets in detecting attacks and anomaly events and in binary classification. When the models that use all the features are evaluated,

- The most successful model in terms of the ACC metric was the stacking ensemble model XGBoost, with an ACC of 0.9163. The XGBoost model achieved this performance value using the standard BoW dataset.
- The most successful model in terms of the FPR metric was the stacking ensemble model AdaBoost, with an FPR of 0.1226. The AdaBoost model achieved this performance value using the standard BoW dataset.
- LR was the most successful model in the testing time metric, with a testing time of 0.0670 seconds. The LR model was achieved using the binary BoW dataset.

When examining the models developed with the selected features from the ADFA-WD based BoW datasets,

- Regarding the ACC metric, the most successful models were the ensemble models XGBoost and AdaBoost, achieving an ACC of 0.9109. These performance values were attained using the standard BoW dataset.
- Concerning the FPR metric, the most successful models were the ensemble models XGBoost and AdaBoost, achieving an FPR of 0.1226. These values were obtained with the standard BoW dataset.

TABLE 7. **Results of experiments performed with all features of ADFA-LD based BoW datasets**

Standard BoW Dataset							
Model	**PRC**	**REC**	**F1**	**FPR**	**ACC**	**Training Time (s)**	**Testing Time (s)**
KNN	0.6462	0.9781	0.7783	0.4623	0.7418	1.4565	4.8532
DT	0.9211	0.9563	0.9383	0.0708	0.9418	5.8913	0.0682
LR	0.9521	0.9781	0.9649	0.0425	0.9671	58.6087	0.1174
RF	0.9323	0.9781	0.9547	0.0613	0.9569	10.0989	0.0928
XGBoost	0.9674	0.9727	0.9700	0.0283	0.9722	73.5626	5.5904
AdaBoost	0.9674	0.9727	0.9700	0.0283	0.9722	73.7034	4.6601
Binary BoW Dataset							
Model	**PRC**	**REC**	**F1**	**FPR**	**ACC**	**Training Time (s)**	**Testing Time (s)**
KNN	0.5773	1.0000	0.7320	0.6321	0.6608	0.9089	2.8401
DT	0.9211	0.9563	0.9383	0.0708	0.9418	6.9260	0.0490
LR	0.9137	0.9836	0.9474	0.0802	0.9494	47.3249	0.0769
RF	0.9184	0.9836	0.9499	0.0755	0.9519	13.8948	0.2734
XGBoost	0.9231	0.9836	0.9524	0.0708	0.9544	58.2466	3.1184
AdaBoost	0.9231	0.9836	0.9524	0.0708	0.9544	57.4651	4.4548
Probability BoW Dataset							
Model	**PRC**	**REC**	**F1**	**FPR**	**ACC**	**Training Time (s)**	**Testing Time (s)**
KNN	0.8876	0.4317	0.5809	0.0472	0.7114	0.0770	3.0732
DT	0.8995	0.9289	0.9139	0.0896	0.9189	25.2534	0.0586
LR	0.9670	0.9617	0.9644	0.0283	0.9671	37.4499	0.0522
RF	0.9275	0.9781	0.9521	0.0660	0.9544	15.0325	0.0993
XGBoost	0.9674	0.9727	0.9700	0.0283	0.9722	67.1284	3.7647
AdaBoost	0.9558	0.9454	0.9505	0.0377	0.9544	67.5366	3.1948
TF-IDF BoW Dataset							
Model	**PRC**	**REC**	**F1**	**FPR**	**ACC**	**Training Time (s)**	**Testing Time (s)**
KNN	0.8889	0.4372	0.5861	0.0472	0.7139	0.0859	4.0084
DT	0.8814	0.9344	0.9072	0.1085	0.9114	21.5065	0.0806
LR	0.9663	0.9399	0.9529	0.0283	0.9569	53.7843	0.1417
RF	0.9188	0.9891	0.9526	0.0755	0.9544	21.8684	0.1297
XGBoost	0.9617	0.9617	0.9617	0.0330	0.9646	86.5145	4.1783
AdaBoost	0.9714	0.9289	0.9497	0.0236	0.9544	80.0019	4.4509

- The best-performing model for the testing time metric was DT, with a time of 0.0015 seconds. This time was achieved using the TF-IDF BoW dataset.

When examining the models developed using all or selected features of the ADFA-WD based BoW datasets,

- Models that used all features generally performed better in terms of ACC and FPR metrics than their counterparts that used selected features across all datasets. Among all datasets, the most successful models in terms of ACC metrics were those XGBoost models that included all dataset features. On the other hand, regarding the FPR metric, the best value on the standard BoW dataset was achieved by XGBoost models with selected features and AdaBoost models with either all or selected features. For the Binary BoW and Probability BoW datasets, the best FPR values were obtained by XGBoost models using all of these datasets' features. Finally, for the TF-IDF BoW dataset, the AdaBoost model that included all features was the most successful regarding the FPR metric.
- In all datasets, models that used selected features had significantly better testing time values compared to their counterparts that used all features.

D. Comparison with Studies in the Literature

Table 11 contains the ACC and FPR performance values for models or frameworks based on the ADFA-LD dataset. Upon examining Table 11,

- It can be observed that the most successful model in terms of ACC and FPR metrics is the RF model in [15]. Although HIDSs in this study achieved lower accuracy compared to the RF in [15], it is essential to note that XGBoost with selected features prioritized computational efficiency and flexibility. This might account for the slight reduction in accuracy and FPR, as this HIDS was optimized for faster processing times, especially in training and testing phases, without compromising overall detection performance. Furthermore, an ensem-

TABLE 8. Results of experiments performed with selected features of ADFA-LD based BoW datasets

Standard BoW Dataset							
Model	**PRC**	**REC**	**F1**	**FPR**	**ACC**	**Training Time (s)**	**Testing Time (s)**
KNN	0.6383	0.9836	0.7742	0.4811	0.7342	0.3257	0.9956
DT	0.9293	0.9344	0.9319	0.0613	0.9367	1.2667	0.0204
LR	0.9521	0.9781	0.9649	0.0425	0.9671	10.9567	0.0248
RF	0.9227	0.9781	0.9496	0.0708	0.9519	2.8898	0.0299
XGBoost	0.9626	0.9836	0.9729	0.0330	0.9747	17.2202	0.9372
AdaBoost	0.9674	0.9727	0.9700	0.0283	0.9722	15.4701	0.9412
Binary BoW Dataset							
Model	**PRC**	**REC**	**F1**	**FPR**	**ACC**	**Training Time (s)**	**Testing Time (s)**
KNN	0.6310	10.000	0.7738	0.5047	0.7291	0.9478	1.1355
DT	0.9105	0.9454	0.9276	0.0801	0.9316	1.9568	0.0190
LR	0.9278	0.9836	0.9549	0.0660	0.9569	9.0705	0.0207
RF	0.9227	0.9781	0.9496	0.0707	0.9519	4.2752	0.0437
XGBoost	0.9286	0.9945	0.9604	0.0660	0.9620	17.7116	1.1231
AdaBoost	0.9323	0.9781	0.9547	0.0613	0.9569	16.0481	1.5222
Probability BoW Dataset							
Model	**PRC**	**REC**	**F1**	**FPR**	**ACC**	**Training Time (s)**	**Testing Time (s)**
KNN	0.8900	0.4863	0.6289	0.0519	0.7342	0.0181	0.6586
DT	0.9043	0.9289	0.9164	0.0849	0.9215	3.9828	0.0596
LR	0.9375	0.9836	0.9600	0.0566	0.9620	7.2691	0.0186
RF	0.9223	0.9727	0.9468	0.0708	0.9494	4.2208	0.0413
XGBoost	0.9674	0.9727	0.9700	0.0283	0.9722	16.3903	0.7978
AdaBoost	0.9672	0.9672	0.9672	0.0283	0.9696	17.4359	0.7500
TF-IDF BoW Dataset							
Model	**PRC**	**REC**	**F1**	**FPR**	**ACC**	**Training Time (s)**	**Testing Time (s)**
KNN	0.9208	0.5082	0.6549	0.0377	0.7519	0.0183	0.6826
DT	0.9144	0.9344	0.9243	0.0755	0.9291	3.0652	0.0176
LR	0.9556	0.9399	0.9477	0.0377	0.9519	7.5922	0.0139
RF	0.9188	0.9891	0.9526	0.0755	0.9544	4.1369	0.0409
XGBoost	0.9471	0.9781	0.9624	0.0472	0.9646	15.9868	0.7927
AdaBoost	0.9471	0.9781	0.9624	0.0472	0.9646	15.5812	0.9086

ble based approach with feature selection might offer better scalability and adaptability for real-time intrusion detection systems, making it a promising candidate for practical deployment. In addition, the trade-off between accuracy and processing time might be more suited to dynamic or large-scale environments where time efficiency is critical.

- It is followed that the second most successful model in terms of the ACC metric is the stacking ensemble based XGBoost model developed using the standard BoW dataset and selected features. Additionally, it appears to have better ACC values compared to the framework in [30].
- It is observed that the second most successful model in terms of the FPR metric is the framework in [30]. It is concluded that the XGBoost model, which has close FPR values with this framework and standard and probability BoW datasets and all features of these datasets are used, and the AdaBoost model, which includes all features on the standard BoW dataset, achieve better ACC values than the framework in [30]. On the other hand, the AdaBoost model using the TF-IDF BoW dataset and all its features demonstrated better performance than the framework from [30] with an FPR value of 0.0236. While most successful models in this study and the framework in [30] show similar FPR values, models in this study achieved higher accuracy, which suggests that the proposed models may offer a more efficient detection of attacks. This indicates that models in this study can deliver competitive performance with potentially more straightforward implementation compared to the framework in [30].

Table 12 compares the performance of models or HIDSs based on the ADFA-WD dataset in terms of ACC and FPR metrics. Examining Table 12, it can be observed these,

- It is concluded that the most successful model in terms of the ACC metric is XGBoost, which uses the standard BoW dataset and all its features.

TABLE 9. Results of experiments performed with all features of ADFA-WD based BoW datasets

Standard BoW Dataset							
Model	**PRC**	**REC**	**F1**	**FPR**	**ACC**	**Training Time (s)**	**Testing Time (s)**
KNN	0.8384	0.9414	0.8869	0.1681	0.8845	1.9334	11.9802
DT	0.8651	0.9338	0.8982	0.1349	0.8982	5.8940	0.2458
LR	0.8276	0.9527	0.8858	0.1839	0.8818	148.8515	0.0919
RF	0.8737	0.9546	0.9124	0.1278	0.9118	34.6784	0.1223
XGBoost	0.8754	0.9565	0.9142	0.1261	0.9163	193.1389	12.0868
AdaBoost	0.8774	0.9471	0.9109	0.1226	0.9109	187.9971	9.9765
Binary BoW Dataset							
Model	**PRC**	**REC**	**F1**	**FPR**	**ACC**	**Training Time (s)**	**Testing Time (s)**
KNN	0.8042	0.8696	0.8356	0.1961	0.8355	1.5192	12.8031
DT	0.8122	0.9074	0.8571	0.1944	0.8545	5.6820	0.0713
LR	0.8285	0.9225	0.8729	0.1769	0.8709	161.4618	0.0670
RF	0.8359	0.9244	0.8779	0.1681	0.8764	60.4979	0.1126
XGBoost	0.8474	0.9130	0.8789	0.1524	0.8791	276.8359	12.6199
AdaBoost	0.8411	0.9206	0.8791	0.1611	0.8782	264.7074	14.9371
Probability BoW Dataset							
Model	**PRC**	**REC**	**F1**	**FPR**	**ACC**	**Training Time (s)**	**Testing Time (s)**
KNN	0.7977	0.9093	0.8498	0.2137	0.8455	1.3783	13.4839
DT	0.8311	0.9395	0.8819	0.1769	0.8791	10.7447	0.0923
LR	0.7935	0.9301	0.8564	0.2242	0.8500	183.6092	0.0962
RF	0.8549	0.9471	0.8987	0.1489	0.8973	45.4147	0.2840
XGBoost	0.8669	0.9357	0.9000	0.1331	0.9000	222.9488	11.4506
AdaBoost	0.8641	0.9376	0.8994	0.1366	0.8991	216.5292	11.6840
TF-IDF BoW Dataset							
Model	**PRC**	**REC**	**F1**	**FPR**	**ACC**	**Training Time (s)**	**Testing Time (s)**
KNN	0.8162	0.9149	0.8627	0.1909	0.8600	0.0944	12.8929
DT	0.8305	0.9357	0.8799	0.1769	0.8773	15.6639	0.1659
LR	0.7933	0.9357	0.8586	0.2259	0.8518	191.2385	0.0739
RF	0.8481	0.9395	0.8915	0.1559	0.8900	41.9776	0.1714
XGBoost	0.8613	0.9509	0.9039	0.1419	0.9027	233.4370	11.6364
AdaBoost	0.8654	0.9357	0.8992	0.1349	0.8991	234.4141	16.2237

- It can be followed that the most successful models in terms of the FPR metric are the stacking ensemble based XGBoost and AdaBoost models, developed using the standard BoW dataset and its selected features.
- It can be observed that the HIDS in [5] is less successful in terms of the FPR metric compared to the models developed in this study, as shown in Table 12.
- In terms of ACC metric, HIDS in [5] is seen to outperform the stacking ensemble based XGBoost and AdaBoost models developed with the standard BoW dataset and the selected features of this dataset by a difference of 0.0001.
- In summary, according to Table 12, it is concluded that the most successful models using ADFA-WD-based BoW datasets developed in this study generally perform better than the HIDS in [5]. With this, when comparing models in this study with the HIDS in [5], models in this study demonstrate significantly better performance in terms of FPR. Specifically, the models that utilize selected features achieve the lowest FPR values, indicating the effectiveness of the feature selection method in minimizing false positives. XGBoost and AdaBoost models developed with the standard BoW dataset and the selected features showed an ACC slightly lower by 0.0001 compared to the HIDS in [5]. This highlights the importance of the feature selection method, which leads to more accurate and reliable intrusion detection with lower FPR and similar ACC values.

The RF in [15], the framework in [30], and the HIDS in [5] were selected for comparison in this study, as they contain similar methods to those developed here. Specifically, the RF in [15] underwent preprocessing using the standard BoW method. In the preprocessing phase of the framework in [30], BoW, n-gram, and TF-IDF methods were applied. While developing the HIDS in [5], n-grams constituted part of the preprocessing phase. Moreover, another reason for selecting the RF in [15], the framework in [30], and the HIDS in [5] was that their performances had been evaluated based on the ACC and FPR metrics. Since the primary objective of this

TABLE 10. Results of experiments performed with selected features of ADFA-WD based BoW datasets

Standard BoW Dataset							
Model	**PRC**	**REC**	**F1**	**FPR**	**ACC**	**Training Time (s)**	**Testing Time (s)**
KNN	0.8248	0.9433	0.8801	0.1856	0.8764	0.2395	2.5312
DT	0.8630	0.9527	0.9057	0.1401	0.9045	1.4769	0.0380
LR	0.7975	0.9527	0.8682	0.2242	0.8609	14.8021	0.0188
RF	0.8618	0.9546	0.9058	0.1419	0.9045	9.4513	0.0640
XGBoost	0.8774	0.9471	0.9109	0.1226	0.9109	30.1907	2.3641
AdaBoost	0.8774	0.9471	0.9109	0.1226	0.9109	22.7040	1.7358
Binary BoW Dataset							
Model	**PRC**	**REC**	**F1**	**FPR**	**ACC**	**Training Time (s)**	**Testing Time (s)**
KNN	0.7300	0.8998	0.8061	0.3082	0.7918	0.0097	0.2035
DT	0.7297	0.9489	0.8249	0.3257	0.8064	0.0900	0.0022
LR	0.7321	0.9659	0.8329	0.3275	0.8136	1.0438	0.0065
RF	0.7334	0.9622	0.8324	0.3239	0.8136	2.4324	0.0492
XGBoost	0.7366	0.9622	0.8344	0.3187	0.8164	1.6297	0.2364
AdaBoost	0.7362	0.9603	0.8335	0.3187	0.8155	1.6962	0.2697
Probability BoW Dataset							
Model	**PRC**	**REC**	**F1**	**FPR**	**ACC**	**Training Time (s)**	**Testing Time (s)**
KNN	0.8000	0.9074	0.8503	0.2102	0.8464	0.0082	0.1895
DT	0.7898	0.9093	0.8453	0.2242	0.8400	0.3884	0.0019
LR	0.6792	0.9527	0.7931	0.4168	0.7609	1.0609	0.0068
RF	0.7979	0.9036	0.8475	0.2119	0.8436	1.5109	0.0367
XGBoost	0.7964	0.9319	0.8589	0.2207	0.8527	4.6610	0.6152
AdaBoost	0.8049	0.8582	0.8307	0.1926	0.8318	6.9679	0.8963
TF-IDF BoW Dataset							
Model	**PRC**	**REC**	**F1**	**FPR**	**ACC**	**Training Time (s)**	**Testing Time (s)**
KNN	0.7915	0.9112	0.8471	0.2224	0.8418	0.0029	0.1675
DT	0.7763	0.9055	0.8359	0.2417	0.8291	0.3071	0.0015
LR	0.6792	0.9527	0.7931	0.4169	0.7609	0.6387	0.0046
RF	0.7823	0.9168	0.8442	0.2364	0.8373	1.7399	0.0255
XGBoost	0.7908	0.9433	0.8603	0.2312	0.8527	5.9861	0.5476
AdaBoost	0.7993	0.8809	0.8381	0.2049	0.8364	3.0592	0.2598

TABLE 11. Comparison on ADFA-LD dataset

Model/Framework	FPR	ACC
Stacking ensemble based XGBoost and AdaBoost with all features	0.0283	0.9722
Stacking ensemble based XGBoost with selected features	0.0330	0.9747
RF in [15]	0.0170	0.9840
Framework in [30]	0.0240	0.9720

TABLE 12. Comparison on ADFA-WD dataset

Model/Framework	FPR	ACC
Stacking ensemble based XGBoost with all features	0.1261	0.9163
Stacking ensemble based XGBoost and AdaBoost with selected features	0.1226	0.9109
HIDS in [5]	0.1330	0.9110

study is the development of various ML models and stacking ensemble HIDS with high ACC and low FPR values, the ACC and FPR values of similar models, frameworks, or HIDS in the literature serve as a crucial criterion for evaluating the ACC and FPR of the most successful models in this study.

On the other hand, the models developed in this study were not compared with similar models in the literature regarding training and testing time. This is because the training and testing times of the models developed in this study were measured on the same environment and hardware. In contrast, the training and testing times of similar models, frameworks, or HIDS in the literature were calculated using different environments and hardware. Therefore, it was considered neither fair nor meaningful to compare the models in this study with similar ones in the literature in terms of training and testing time. Additionally, the aim was to compare the training and testing times of the models developed using all features with those of the equivalent models that contain the selected features. Thus, the positive impact of the feature selection algorithm in Algorithm 1 on training and testing