A Phishing URL Classification Technique using Machine Learning Approach

Manish Tiwari, Tripti Arjariya

Abstract: The phishing attack is one of the very common attacks deployed using the social engineering techniques. The attack tries to capture the victim's personal and sensitive information to trick and can results in terms of financial and social reputation loss. In this presented work the main focus is to investigate the phishing techniques and their detection approaches. In this context first a review on recently contributed URL based phishing attack detection and prevision techniques is prepared. Further based on the suitable techniques a new data mining based model is proposed for implementation. The proposed model first take training on phish tank database URLs and then identify the similar pattern based URLs in two classes legitimate and phishing. First the dataset is preprocessed and the features are computed. The computed features are then transformed in terms of transactional database and association rules are prepared. To generate the association rules the apriori algorithm and FP-Tree algorithm is employed. Based on conducted experiments, the performance the FP-Tree based classification technique much efficient and accurate as compared to apriori algorithm, because the apriori algorithm is much time expensive then the FP-Tree. Finally the future extension of the work is also suggested.

Keywords: phishing detection, URL classification, association rule mining, rule based classification, apriori algorithm, FP-Tree algorithm.

I. INTRODUCTION

Communication technologies are growing rapidly, not only the traditional communication methods such SMS and voice calls are increasing the new methods of communication is also enabled in recent years such as email, MMS, social media messages. Peoples may use these methods in various different manners i.e. publishing contents, advertisements, promotions and many others. But not always people use these channels legitimately sometimes malicious users tried to capture others sensitive and private information. Such kind of fraud is known as phishing. Phishing is an act of cyber crime where using false commitments the private and confidential information is still by attacker. This result the end user suffers for financially or socially. It is a serious crime [1]. In this work the phishing technique investigation is the main aim. Therefore different available techniques of phishing detection and prevention are involved in this study. But awareness of end users can only the way by which we can prevent the attacks. The classical techniques are mainly two types first blacklist or white list based and second is based on machine learning or pattern recognition. Among the list management based techniques are expensive in terms of computational resource cost therefore the proposed technique is developed using machine learning. The proposed technique helps to understand the phishing URL patterns and recognize the similar pattern URLs in terms of legitimate and phishing. The first preprocess the URLs and then essential features are extracted from phishing URLs. These phishing URLs are obtained from an authentic data source namely phish tank database. Finally the training of algorithm is carried out and classifying the real world web URLs in terms of phishing or legitimate. The proposed approach is promising for accurate phishing URLs identification.

II. UASN ARCHITECTURES

The aim of the work is to investigate the phishing attack. Additionally design a machine learning model that can recognize the phishing URL patterns and can generate an alarm to user. This chapter provides the understanding of the proposed system which is required to develop for classifying URLs accurately and efficiently.

A. System Overview

Phishing is an act of cyber crime and it becomes much serious when the data is disclosed in public domain by some phishing attack or become an act of financial fraud. Therefore it is required to identify the attack. In most of the phishing cases a malicious URL is deployed on the target person's device. It may be in format of some emails, SMS, MMS or any social media networks such as Facebook, Linkedin, WhatsApp and others. The victim visits such malicious URL which is falsely created by the attacker. The victim provides his/her personal details such as bank account details, credit card details and others. On the other hand the attacker gets these details to blackmail you or conducting the financial losses. Therefore the awareness is only the key to prevent such kind of attacks. But there are various efforts are also available by which we can recognize such kind of links by using some kinds of tools. There are mainly two kinds of techniques available for performing such task first is based on list which consist of some previously reported URLs and cross verify the link which is time consuming and need to update database regularly. On the other hand some techniques are also developed by which we can recognize the URLs.

Revised Manuscript Received on January 08, 2021.
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In these techniques the machine learning or data mining techniques are used. The machine learning based techniques are first Learn on these patterns and then classify the URLs according to their learned patterns.

Therefore we are motivated to design a machine learning model which can identify the phishing URL patterns by analyzing them. This section offers the overview of the proposed system which is needed to be design. Additionally the next section demonstrates the system design and their components with their functional aspects.

B. Methodology

The required model for phishing URL classification is demonstrated in figure 1. Additionally their components are also provided. This section involves the details about the provided functional details.

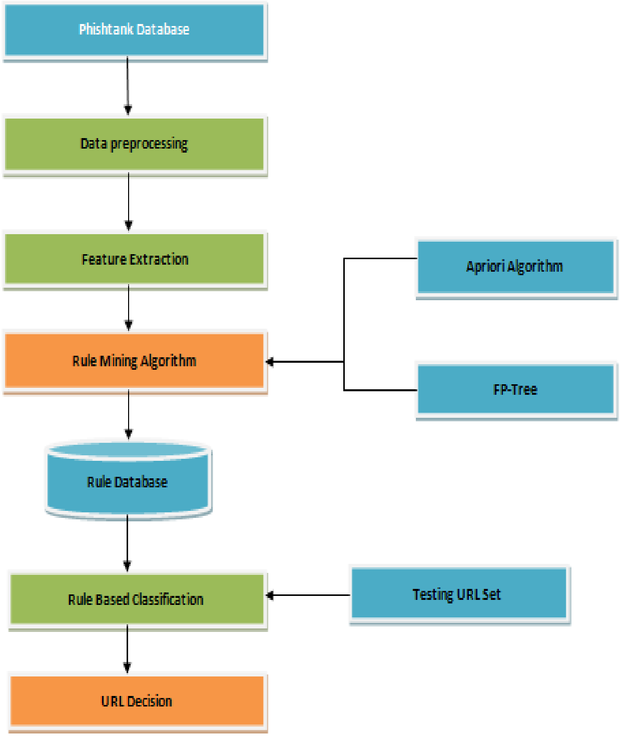


Figure 1 proposed system architecture

Phish tank database: the machine learning techniques requires the initial training examples to learn with patterns. In this experiment the phish tank dataset is used as initial input for the system. The phish tank dataset is organized by different cyber security institutions. It is collection of phishing URLs that are recently reported. The dataset includes various different information such as phish ID, URL, phish detail URL, submission date, verification time, online status, target. The entire information is available either as download in CSV format or using web service API for directly utilizing with an application. In this system we are utilizing the CSV data for training.

Data preprocessing: as we discussed the dataset contains various information about the phishing URLs but the entire information in the given dataset is not useful for analysis purpose. Therefore in this process we reduce the unused attributes from the dataset and preserve the URL for further use. The preprocessing basically aimed to clean the dataset and improve the quality of data. Thus in this process we can used different techniques to recover the required information from entire set of data.

Feature extraction: the pattern learning algorithms need some essential features to use in developing the data model. But after preprocessing we find just URLs thus we need to compute the different properties from the URL which can be used for representing the phishing URL properties. Thus the features defined in [2] are used for learning with the pattern learning algorithm. Some of the essential features are reported as:

1. length of the host URL
2. number of slashes in URL
3. dots in host name of the URL
4. number of terms in the host name of the URL
5. special characters
6. IP address
7. Unicode in URL
8. transport layer security
9. Sub-domain
10. certain keyword in the URL
11. top level domain
12. number of dots in the path of the URL
13. hyphen in the host name of the URL
14. URL length

The above discussed properties are calculated from each URL using the given constrains. After applying the given constraints a value is computed. The computed values for each URL are stored separately. After computation of the features form each URL return 14 values. These values are compared against a threshold value. The obtained feature values If satisfying the threshold then the feature is recognize it as 1 otherwise it is 0. Therefore the entire URLs are transformed into a binary 2D vector.

Rule mining algorithms: in this phase the 2D vector is produced as input to the system. Additionally we need to mine the rules using these features. In this context we are proposing to employ the association rule mining techniques namely apriori algorithm and FP-Tree algorithm. Both the techniques are requires the Itemset and transaction sets to mine the data. Therefore first we need to recover the transaction set and item set. In order to understand the process of transaction set and itemset extraction let an example feature vector table as given in table 1.

Table 1 Example Feature Table

A	B	C	D	E	F
1	1	0	0	1	0
1	0	1	0	1	1

Using the given table 1 we can conclude the set of symbols {A, B, C, D, E, F} can works as itemset additionally using two instances of features we can create the following two transactions:

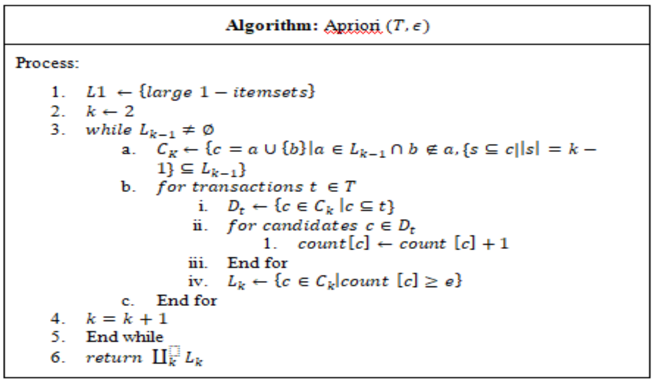
Table 2 Transaction Sets

Transaction ID	Transactions
1	A, B, E
2	A, C, E, F

The table 2 shows the transaction sets which can be defined using the table 1.

Apriori algorithm: Apriori algorithm is easy and very simple, to mine frequent itemsets in a transactional database. The algorithm makes searches in database to find frequent itemsets where k itemsets are used to generate k+1- itemsets. Each k-itemset must be greater than or equal to minimum support threshold to be frequency. Otherwise, it is called candidate itemsets. In the first, the algorithm scan database to find frequency of 1-itemsets that contains only one item by counting each item in database. The frequency of 1-itemsets is used to find the itemsets in 2- itemsets which in turn is used to find 3-itemsets and so on until there are not any more k-itemsets. If an itemset is not frequent, any large subset from it is also non-frequent; this condition prune from search space in database.

Table 3 Apriori Algorithm



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Algorithm: Apriori $(T, \epsilon)$

Process:
    1. $L1 \leftarrow \{large\ 1 - itemsets\}$
    2. $k \leftarrow 2$
    3. $while\ L_{k-1} \neq \emptyset$
        a. $C_K \leftarrow \{c = a \cup \{b\} | a \in L_{k-1} \cap b \notin a, \{s \subseteq c | |s| = k - 1\} \subseteq L_{k-1}\}$
        b. $for\ transactions\ t\ \in T$
            i. $D_t \leftarrow \{c \in C_k\ | c \subseteq t\}$
            ii. $for\ candidates\ c \in D_t$
                1. $count[c] \leftarrow count\ [c] + 1$
            iii. End for
            iv. $L_k \leftarrow \{c \in C_k | count\ [c] \geq e\}$
        c. End for
    4. $k = k + 1$
    5. End while
    6. $return\ \coprod_k L_k$
```

FP-Tree algorithm: Frequent Pattern Tree is a tree-like structure that is made with the initial itemsets of the database. The purpose of the FP tree is to mine the most frequent pattern. Each node of the FP tree represents an item of the itemset. The root node represents null while the lower nodes represent the itemsets. The association of the nodes with the lower nodes that is the itemsets with the other itemsets is maintained while forming the tree. The frequent pattern growth method lets us find the frequent pattern without candidate generation. Let us see the steps followed to mine the frequent pattern using frequent pattern growth algorithm:

1. The first step is to scan the database to find the occurrences of the itemsets in the database. This step is the same as the first step of Apriori. The count of 1-itemsets in the database is called support count or frequency of 1-itemset.
2. The second step is to construct the FP tree. For this, create the root of the tree. The root is represented by null.
3. The next step is to scan the database again and examine the transactions. Examine the first transaction and find out the itemset in it. The itemset with the max count is taken at the top, the next itemset with lower count and so on. It means that the branch of the tree is constructed with transaction itemsets in descending order of count.

The next transaction in the database is examined. The itemsets are ordered in descending order of count. If any itemset of this transaction is already present in another branch (for example in the 1st transaction), then this transaction branch would share a common prefix to the root. This means that the common itemset is linked to the new node of another itemset in this transaction. Also, the count of the itemset is incremented as it occurs in the transactions. Both the common node and new node count is increased by 1 as they are created and linked according to transactions.

4. The next step is to mine the created FP Tree. For this, the lowest node is examined first along with the links of the lowest nodes. The lowest node represents the frequency pattern length 1. From this, traverse the path in the FP Tree. This path or paths are called a conditional pattern base. Conditional pattern base is a sub-database consisting of prefix paths in the FP tree occurring with the lowest node (suffix).
5. Construct a Conditional FP Tree, which is formed by a count of itemsets in the path. The itemsets meeting the threshold support are considered in the Conditional FP Tree.
6. Frequent Patterns are generated from the Conditional FP Tree [15].

Rule database: both the algorithms consume the itemsets and transaction sets and generate the rules according to the above discussed process or algorithms. These rules are preserved in a database for utilizing the rules for classifying the testing URLs.

Test dataset: after preparing the rules database for classification task it is required to test the model for identifying the model is working properly or not. Thus an additional test dataset is prepared which contains different amount of phishing URLs and also included some normal web URLs from authentic source.

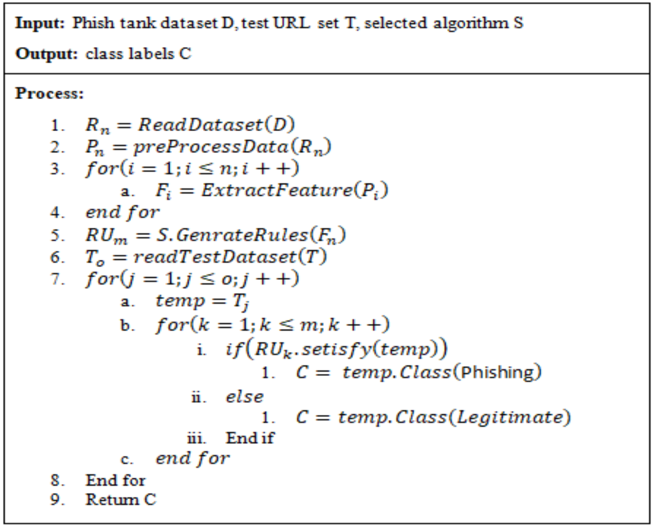
Rule Based Classification: this function accepts the test dataset and the rule database. Additionally using the prepared rules the system validates each URL for finding or predicting the class labels i.e. legitimate or phishing.

URL decision: that is the final outcome of the proposed model which produces the outcome or decision about the test URLs. In other words the model returns the class labels for the testing URLs in terms of phishing or legitimate.

C.Proposed Algorithm

The steps of the proposed algorithm are given in table 4. That includes the steps and the relevant processes involved in the proposed model.

Table 4 Proposed algorithm



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Input: Phish tank dataset D, test URL set T, selected algorithm S
Output: class labels C

Process:
    1. $R_n = ReadDataset(D)$
    2. $P_n = preProcessData(R_n)$
    3. $for(i = 1; i \leq n; i + +)$
        a. $F_i = ExtractFeature(P_i)$
    4. $end\ for$
    5. $RU_m = S.GenrateRules(F_n)$
    6. $T_o = readTestDataset(T)$
    7. $for(j = 1; j \leq o; j + +)$
        a. $temp = T_j$
        b. $for(k = 1; k \leq m; k + +)$
            i. $if(RU_k.setisfy(temp))$
                1. $C =\ temp.Class$(Phishing)
            ii. $else$
                1. $C = temp.Class(Legitimate)$
            iii. End if
        c. $end\ for$
    8. End for
    9. Return C
```

III. RESULTS ANALYSIS

The proposed machine learning based phishing URL classification technique is implemented successfully and need to evaluate the performance for justifying the implemented system. This chapter reports different performance parameters which are implemented for describing the efficiency and accuracy of the implemented system.

A. Accuracy

The accuracy is a measurement of correctness of the classification system. In this context the total correctly recognized phishing URLs using the proposed method is termed here as the accuracy of the proposed phishing detection model. That is computed using the following formula:

$$accuracy = \frac{total\ correctly\ recognized\ URLs}{total\ URLs\ to\ classify} X100$$

Table 5 accuracy (%)

Dataset Size	Apriori Algorithm	FP-Tree Algorithm
50	76.3	77.9
100	78.8	79.5
150	80.2	81.7
200	81.6	84.2
250	83.2	86.6
300	84.5	89.4
500	88.39	91.8

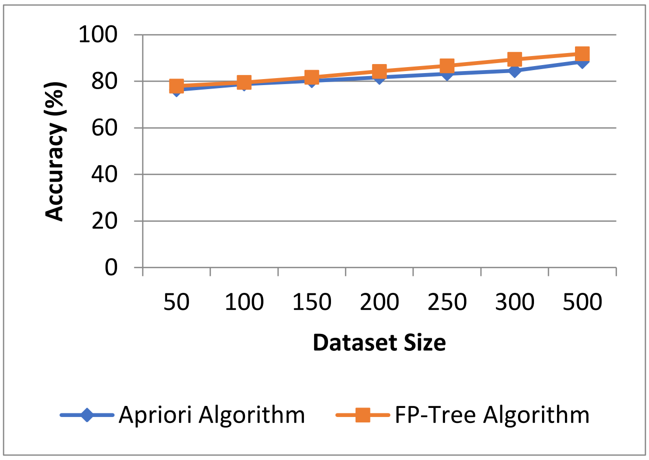

Figure 2 accuracy

The performance of the proposed model in terms of accuracy percentage is given in figure 2 and table 5. The line graph representation of table 5 is given using figure 2, that table contains the observations of experiments of increasing amount of data size. The X axis of the diagram shows the dataset size and Y axis shows the obtained accuracy of the algorithms. In this work two different techniques of association rule mining is used for classifying the URLs, among the FP-Tree algorithm is demonstrating higher accuracy as compared to the traditional technique.

B. Error Rate

The error rate of a classification algorithm is measurement of misclassification rate. Thus the total misclassified URLs are termed here as the error rate of algorithm. That is measured using the following equation:

$$Error\ Rate = \frac{total\ misclassified\ URLs}{Total\ URLs\ to\ classify} X100$$

Or

$$Error\ rate = 100 - accuracy$$

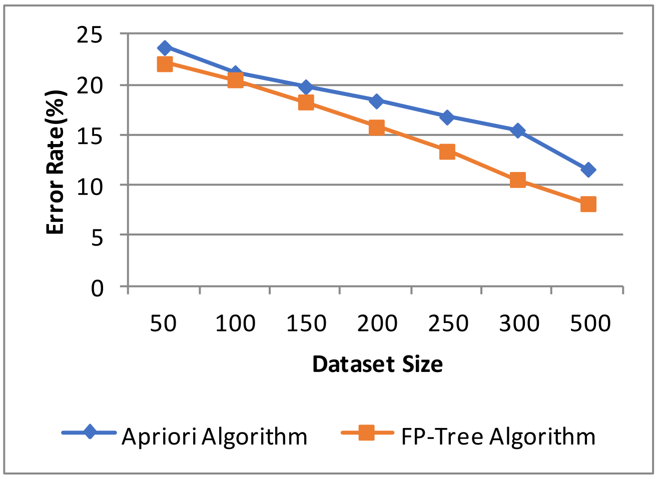

Figure 3 error rate

Table 6 error rate (%)

Dataset Size	Apriori Algorithm	FP-Tree Algorithm
50	23.7	22.1
100	21.2	20.5
150	19.8	18.3
200	18.4	15.8
250	16.8	13.4
300	15.5	10.6
500	11.61	8.2

The figure 3 and table 6 shows the performance of phishing URL classification model using apriori and FP-Tree algorithm. The collected experimental observations are reported in table 6 and the visualization of line graph for the same is given in figure 3. The X axis of this diagram contains the dataset size and Y axis shows the percentage error rate in the system. According to the given results the performance of the FP-Tree is much effective than the Apriori algorithm.

C. Memory Usages

The memory usages are also known as space complexity of the algorithm. That indicates the utilized memory resource during the execution of the target algorithm. It is measured using the following formula in JAVA technology.

$$\mathit{Memory\ Usage} = \mathit{total\ memory} - \mathit{free\ memory}$$

The memory usages of the model are demonstrated in both figure 4 and table 7. In the table 7 the experimental observations are given with increasing amount of data. The size of dataset used in experiments are given in X axis. Additionally the measured performance of both the algorithm is given in Y axis and measured in terms of KB (kilobytes).

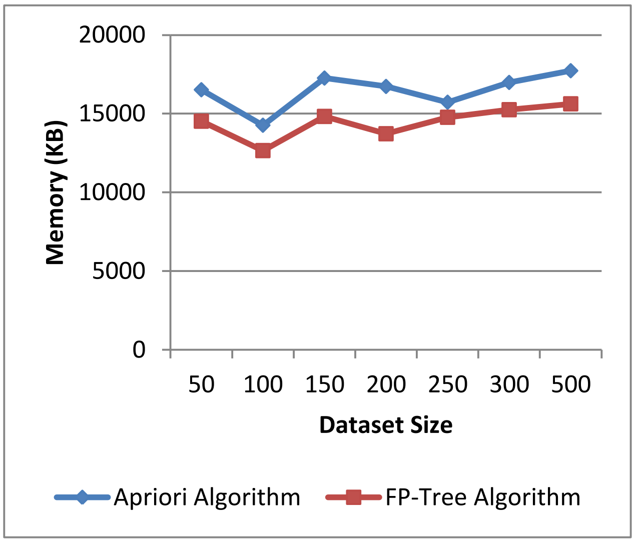

Figure 4 memory usages

Table 7 Memory Usages

Dataset Size	Apriori Algorithm	FP-Tree Algorithm
50	16522	14525
100	14267	12658
150	17264	14827
200	16732	13726
250	15729	14774
300	16986	15254
500	17729	15628

According to obtained experimental patterns the FP-Tree algorithm is efficient as compared to apriori algorithm in terms of memory usages.

D. Time Consumption

The time consumption of the algorithm is also known as the time complexity of the algorithms. The time consumption of the algorithm can be measured using the following formula:

$$\mathit{time\ consumed} = \mathit{end\ time} - \mathit{start\ time}$$

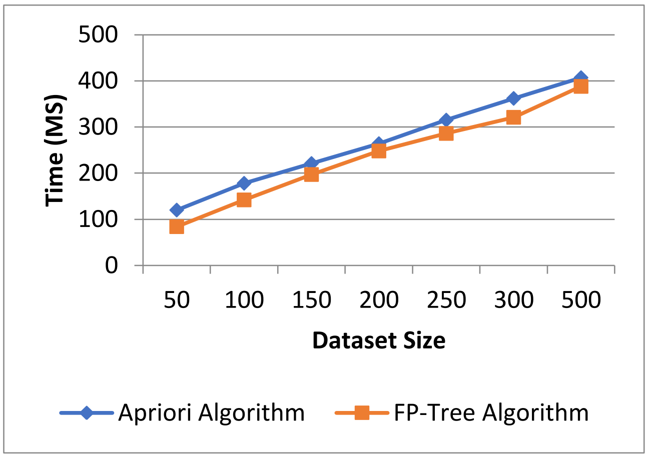

Figure 5 Time Consumption

The performance of the system for URL classification is given using the figure 5 and table 8. Here for measuring the performance of both the algorithms milliseconds are used as scale. The X axis of the line graph shows the dataset size and Y axis demonstrate the utilized time for execution of the target algorithms. According to the obtained results the performance of the FP-tree is much effective as compared to Apriori algorithm due to less time consumption. Thus the FP-tree based model is much efficient as compared to apriori algorithm.

Table 8 Time consumption

Dataset Size	Apriori Algorithm	FP-Tree Algorithm
50	120	84
100	178	142
150	221	197
200	264	248
250	315	286
300	362	321
500	407	388

IV. CONCLUSION & FUTURE WORK

The proposed work is aimed to apply the machine learning techniques for detecting phishing attacks by classifying the URLs according to the recovered features from URL. This work is accomplished successfully additionally the summary of the work is discussed as conclusion and the future extension is also reported.

A.Conclusion

The data mining and machine learning techniques are hugely accepted now in these days in various decision making, pattern identification and prediction tasks.

In this context various kinds of techniques used among them rule based classification technique is one of the effective method. In this work the rule based learning model is demonstrated for classify the malicious URLs. These malicious URLs are deployed in various ways to victim's device for visiting it and capturing sensitive and private information. Such kind of cyber crime is known as the phishing. Therefore the proposed work is dedicated to design an efficient and accurate phishing detection technique. In this presented work we are designing a phishing detection model therefore first we used apriori algorithm for designing it. First the dataset is preprocessed to recover the reported URLs as phishing. After preprocessing of the dataset we extract the features form URLs. These features are used for learning and preparing the classification rules. These classification rules are further used with the new URLs to identify their class labels (i.e. phishing, or legitimate). After that due to higher resource consumption and long running time the model is again designed with the help of FP-tree algorithm. Additionally a comparative performance study is prepared for justifying the results among both the classification techniques. In this experiment the phish tank database is used. The implementation of the proposed work is carried out using JAVA technology. Additionally for preserving the performance parameters the MySQL server is used. According to the obtained performance the mean performance summary is also computed and reported in table 9.

Table 9 performance summary

S. No.	Parameters	Apriori algorithm	FP-Tree
1	Accuracy	81.71 %	84.44 %
2	Error rate	18.29 %	15.55 %
3	Memory usage	16461.28 KB	14484 KB
4	Time consumption	266.71 MS	238 MS

According to the obtained performance there are two techniques namely Apriori and FP-Tree algorithm is implemented for rule based phishing URL classification. According to obtained performance the FP-Tree based URL classification provides the higher accuracy and also demonstrate less resource consumption. Thus the proposed model is promising and acceptable for future extension.

B. Future Work

The proposed phishing URL classification system is successfully implemented and their performance is also recorded. According to the performance obtained the current model is acceptable with 91% of accurate detection rate but still the system need some additional improvement for finding more effective system development. Therefore the following future extensions are proposed for further development.

1. The rule based classification system may consume significant amount of time for identifying the URL class labels additionally large number of rules also increases the amount of time
2. The ensemble learning technique is one more effective method which improve the classifiers performance thus in near future we have tried to implement the technique using ensemble learning method

REFERENCES

1. T. D. Baruah, "Effectiveness of Social Media as a tool of communication and its potential for technology enabled connections: A micro-level study", International Journal of Scientific and Research Publications, Vol 2, Issue 5, May 2012
2. M. Sameen, K. Han, S. O. Hwang, "PhishHaven—An Efficient Real-Time AI Phishing URLs Detection System", VOLUME 8, 2020, IEEE
3. K. Amarendra, "A Survey on Data Mining and its Applications", International Journal of Emerging Trends & Technology in Computer Science, Volume 3, Issue 3, May-June 2014.
4. S. Mukherjee, R. Shaw, N. Haldar, S. Changdar, "A Survey of Data Mining Applications and Techniques", International Journal of Computer Science and Information Technologies, Volume 6, Issue 5, 2015, pp. 4663-4666
5. S. P. Bora, "Data mining and ware housing." In Electronics Computer Technology, 2011 3rd International Conference on, volume 1, pp. 1-5. IEEE, 2011.
6. N. Jain, V. Srivastava, "Data Mining Techniques: A Survey Paper", IJRET: International Journal of Research in Engineering and Technology, Volume: 02 Issue: 11, Nov-2013.
7. S. Sumathi, S. N. Sivanandam, "Introduction to data mining and its applications", Volume 29, Springer, 2006.
8. I. H. Witten, E. Frank, M. A. Hall, "Data Mining: Practical Machine Learning Tools and Techniques", (3rd Ed.), Elsevier, 30 January 2011.
9. Petre, Ruxandra - Stefania, "Data mining in cloud computing", Database Systems Journal 3.3 (2012): 67-71.
10. F. Sebastiani, "Machine learning in automated text categorization", ACM Computing Surveys, Volume 34, Number 1, 2002, pp. 1–47
11. S. B. Navathe, E. Ramez, "Data Warehousing and Data Mining", in "Fundamentals of Database Systems", Pearson Education pvt Inc., Singapore, 2002, 841-872.
12. D. Watson, T. Holz, and S. Mueller, "Know your enemy: Phishing, behind the scenes of Phishing attacks", The Honeynet Project & Research Alliance
13. T. Jagatic, N. Johnson, M. Jakobsson, F. Menczer, "Social Phishing, Community. ACM, Vol. 50, No. 10 (pp. 94-100).
14. R. Basnet, S. Mukkamala, A. H. Sung, "Detection of phishing attacks: A machine learning approach", Soft Computing Applications in Industry, Springer Berlin Heidelberg, PP. 373-383, 2008.
15. H. Tout, W. Hafner, "Phishpin: An identity-based anti-phishing approach" in proceedings of international conference on computational science and engineering, Vancouver, BC, pages 347-352, 2009
16. I. R. Ahamid, J. Abawajy, T. Kim, "Using Feature Selection and Classification Scheme for Automating Phishing Email Detection" Studies in Informatics and Control 22(1): pp. 61-70, March 2013
17. V. Suganya, "A Review on Phishing Attacks and Various Anti Phishing Techniques", International Journal of Computer Applications, Volume 139 – No.1, April 2016.
18. V. Shreeram, M Suban, P Shanthi, K Manjula, "Antiphishing detection of phishing attacks using genetic algorithm", Proceedings of the International Conference on Communication Control and Computing Technology, pp. 447-450, 2010
19. J. Chen, C. X. Guo, "Online Detection and Prevention of Phishing Attacks", Proceeding of the First International Conference on Communication and Networking in China, Beijing, pp. 1-7, 2007.
20. M. Dunlop, S. Groat, D. Shelly, "Goldpolish: Using Images for Content-based Phishing Analysis, In Proceedings of the Fifth International Conference on Internet Monitoring and Protection, Barcelona, pp. 123-128, 2010.

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I am Manish Tiwari from Bhopal. I am a student of M. Tech computer science & application in Bhabha Engineering Research Institute, Bhopal from year 2013 to present. I had done my 10th in 2005 and I had also done my 12th in 2008 (Physics, Chemistry & Mathematics). I had done Bachelor Of Engineering in Computer Science from Gargi Institute Of Science & Technology, Bhopal Madhya Pradesh.

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I am Dr. Tripti Arjariya from Bhopal. I am currently working as a Dean & Professor in Computer Science & Application department in Bhabha university From 01-01-2018 to till date.

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As I am having good teaching and management skills. I was appointed for valuation of copies and paper setters for the various universities for e.g. Dr. Hari Singh Gour central University, Sagar, Rajiv Gandhi Technical University, Bhopal and many more.

All the above skills helped me to achieve various milestone in my life like I have **2 PATENT** done and **59 research papers** published in International and National conferences and journals. I published **2 Books also**.

I Organized a **national Conference** on Emerging Trends of Engg, and organized a **Faculty development Program** on Machine Learning & Big Data Science (2019).

About my family backround my Father's name is Shri R.K. Arjariya and mother's name is Smt. Vidhya Arjariya. My Nationality is Indian and I can communicate in Hindi and English languages.