CNN-HMM Model for Real Time DGA Categorization

Aimen Mahmood[1], Haider Abbas[2][a] and Faisal Amjad[1][b]
[1]*National University of Sciences and Technology, Islamabad, Pakistan*
[2]*KTH-Royal Institute of Technology, Stockholm, Sweden*

Keywords: Domain Generation Algorithms, Domain Fluxing, Classification of DGA, Word-List DGA, Pseudo Random DGA, Convolution Neural Network.

Abstract: To remotely control the target machine, hackers manage to establish a connection between victim and their Command and Control server(C2). In order to hide their C2 they generate domain names algorithmically. Such algorithms are called Domain Generation algorithms(DGA). These algorithmically generated domain names are either gibberish as the characters are generated and concatenated randomly, or pure dictionary words or the combination of the two. This paper presents an algorithm that classifies the DGA running on a compromised system either as gibberish, dictionary oriented or the mixed one, in real time. The proposed algorithm consists of two distinct modules i) Network forensics to detect the DGA ii) Classification of the DGA using the combination of Hidden Markov Model and Convolution Neural Network in real time. The algorithm is trained and tested against more than 0.21 million samples taken from more than 50 different DGAs. The algorithm gives as good as 99% accuracy for all types of DGAs. In addition it can detect zero day DGA as well as multiple DGAs running on a system.

1 INTRODUCTION

Nowadays the organizations are opting the paperless technology to support the green environment, but making the data more vulnerable to the cyber attacks. On the contrary, adversaries are becoming more active by producing sophisticated malicious attacks. The most damaging attacks like credential stealing, ransomware, banking trojans and many more are conducted through a malicious remote server called Command and Control(C2) servers. In such attacks, the compromised system try to establish a remote connection with a C2, which then remotely controls the infected system.

Malware is an unwelcome software which enters into the victim system suspiciously. Normally the IP address or the domain name of C2 is hard-coded in the malicious binary file, inturn can be blocked easily. However, to keep their C2 alive and active, bad actors have opted a sophisticated technique called domain fluxing in which the domain names are generated dynamically by in-cooperating ”Domain Generation Algorithm” (DGA) (Vormayr et al., 2017). Such domain names are random in nature as they are based on a seed value. If the seed value is known, then the security analysts can predict the future domain names and block them in advance.Alternatively adversaries put all their effort to use such a seed that also changes dynamically.

Figure1 shows the complete process of DGA. Same DGA algorithm, with the same seed, executes at both ends ie attacker as well as infected system. Usually date/ time is used as a seed value, which is taken either from an online source or through the http response. In the simplest case malware generates the alphabets/digits randomly and concatenate them into a second level domain name(SLD) of a fixed length, defined in the algorithm. Once being fully generated then top level domains (TLD), which are predefined, are concatenated with SLD to make a fully qualified domain name(FQDN). Usually it generates a huge list of domain names but only few of them are registered, with a shorter time to live(TTL). The victim system sends the DNS queries to the DNS server for all those domain names. If the domain name is not found in DNS server, it is forwarded to the root name server as depicted in figure 1. In case of un registered domain names, Non existent domain name(NX domain), a prominent characteristic of DGA, is returned as a response. However if a rendezvous point is achieved

[a] https://orcid.org/0000-0002-2437-4870
[b] https://orcid.org/0000-0003-4912-6168

Mahmood, A., Abbas, H. and Amjad, F.
CNN-HMM Model for Real Time DGA Categorization.
DOI: 10.5220/0012136800003555
In *Proceedings of the 20th International Conference on Security and Cryptography (SECRYPT 2023)*, pages 822-829
ISBN: 978-989-758-666-8; ISSN: 2184-7711

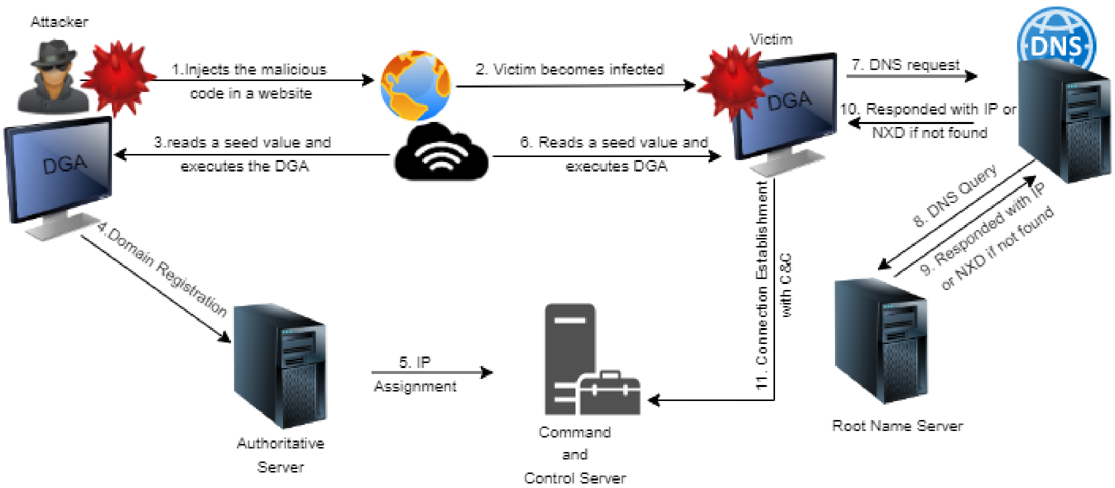


Figure 1: Overview of Domain Generation Algorithm.

the IP address is returned to the victim system, thus establishing the connection.

Here, as characters and digits are generated and concatenated randomly thus leading to a gibberish domain names(R-DGA), another lead indicator of DGA. Most of the researchers have used them in their detection systems. Being easily detectable, so now malicious authors are using dictionary words in the domain names(W-DGA), thus making them harder to detect.

DGAs are incorporated in various types of malware including banking Trojans(Oppenheim et al., 2017), adware, malware for IoT (Antonakakis et al., 2017),(Vinayakumar et al., 2020), Botnets(Wang et al., 2017), malware for supply chains (Labs, 2017) etc. Over the last decade, banks have become the soft target for the banking Trojans(Atzeni et al., 2020). These Trojans steal the credentials of the customers and may also empty their accounts. Emotet(Bromium, 2019), a banking Trajan, first seen in 2014, is still active and becomes the one of the nastier Trojans due its polymorphic nature(Technologies, 2020) and it incorporates DGA. Till date up to 50000 domain names have been used by it. Mirai is another malware which has targeted IoT(Antonakakis et al., 2017) and its variants are still active.

Malware with domain fluxing are ordinarily detected on the basis of their DNS behavior and the lexical features of SLD . In this paper we are presenting an algorithm to detect DGA by monitoring the DNS response followed by hybrid model of Hidden Markov Model (HMM) and Convolution Neural Network (CNN) to categorize the given SLD into R-DGA, W-DGA or the mixture of both. Our contributions towards this paper are listed as under:

- It presents an algorithm which detects a DGA by using live Network forensics.
- The algorithm extracts the domain name from the DNS query and tokenize it using Hidden Markov model, an extension of probabilistic model, into its constituent words or subwords if exists any.
- The extracted subwords/words alongwith their probabilities are then used for feature engineering. Multiple features, extracted from subwords are fed into CNN for classification.
- We have tested the algorithm for more than 56 different DGAs having the accuracy greater than 99%.

The paper is organized in 5 sections. Section II gives the literature review, section III explains the proposed framework. Section IV briefly analyzes the results and performance. Finally the paper is concluded in section V.

2 LITERATURE REVIEW

DGA based malware are more sophisticated and dangerous as their C2 remain untraceable due to the randomness inherited by their SLDs. Taxonomy of such SLD depend on a seed which can be dynamic in nature. Various techniques have been proposed so far to detect and classify these DGAs in real time or in close to real time. Zaho et al., based on semantic features of SLD, developed a DGA detection system(Zhao et al., 2019). These semantic features include entropy, length of the SLD, ratio of vowels, consonants, digits etc. Malicious Domain names are detected on the basis of N-gram and then are tested against the Alexa dataset (Internet, 2018).

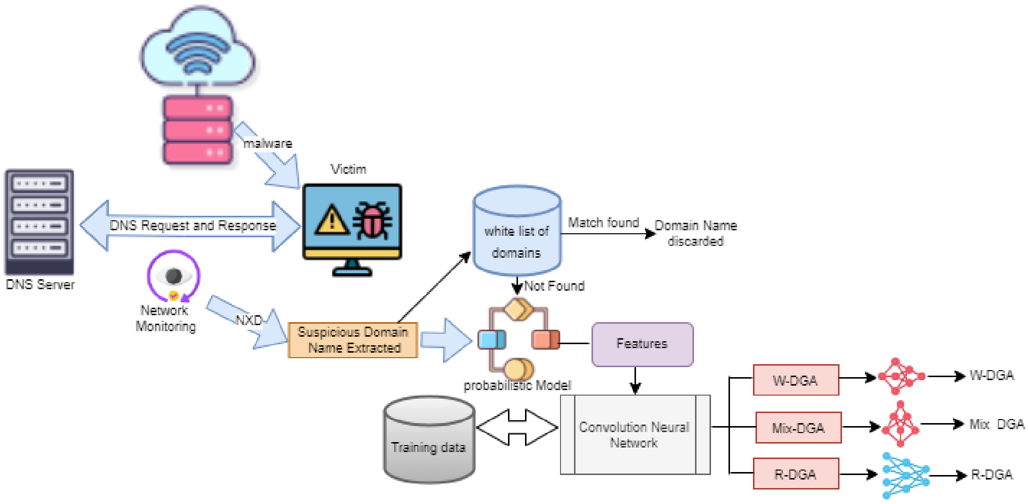


Figure 2: Overview of DGA Detection Algorithm.

DGAs are usually deployed for Bot network. All the bots generate the DNS requests for the same domain names within a small time interval. The detection algorithm tries to identify a pattern among all these DNS queries, as they may inherit some similarity(Wang et al., 2017). Although the detection accuracy in real time is high, but the approach is not suitable for the single system.Using the same approach Erquiaga et al. (Erquiaga et al., 2016) considered the behavioral models of DNS during a specific time window to detect DGAs.

Grill et al. (Grill et al., 2015) based their system on NetFlow data, combination of a source IP and port and a destination IP address and port, time stamps, byte counters and packet counters. S. Tian et al. (Tian et al., 2016) used mobile web traffic for DGA detection. The detection was based on textual features, statistical features and DNS traffic. The textual and semantic features are actually humanly crafted features, so the detection systems, based on these features, may perform adversely for a zero day attack. And also a minor change in the DGA algorithm will be effective in bypassing such detection systems.

Researchers have deployed machine learning algorithms using the above mentioned features. These include deep neural networks, random forest(Yan et al., 2020), decision trees(Pereira et al., 2018), clustering (Amini, 2008),(Bisio et al., 2017) and (Pereira et al., 2018), support vector machines(SVM) (Wang et al., 2018), Recurrent Neural Networks(RNN), CNN(Hwang et al., 2020), Long short term memory(LSTM)(Shahzad et al., 2021), autoencoders(Skansi, 2018). (Wang et al., 2018) has deployed SVM to classify the DGA domain names from benign domain names. The algorithm takes lexical features like entropy, length of SLD, vowels, ratio of consonants and the digits for classification. Although the data set was small but the algorithm gave accuracy as good as 89%. F. Bisio et al. (Bisio et al., 2017) analyzes the DNS traffic using K-means clustering in a near-real-time in order to detect DGA. (Xu et al., 2019) has developed a model based on N-gram which works for both R-DGA and W-DGA. The model gives more than 98% accuracy both on random an as well as wordlist domain names. But they have only tested on 16 different DGA malware. (Shahzad et al., 2021) deployed LSTM but the detection was focused on R-DGA only. CNN (Hwang et al., 2020) based on linguistic features which worked well for R-DGA only. Researchers have deployed deep neural networks (Ren et al., 2020) but may only detect W-DGA.

Although machine learning algorithms are best for intelligent detection but their accuracy may suffer due to imbalance of samples.(Liu et al., 2020) provided a technique to handle imbalance sample set and thus improved the accuracy. It is inferred from the literature that the above mentioned algorithms either focus on R-DGA or on W-DGA but not on both and their accuracy may suffer due to imbalanced training set. In addition, there exists another DGA which is actually the mixture of both ie the domain names consists of gibberish as well as dictionary words. It is inferred from the above discussion that one machine learning algorithm may work well for one category of DGA but may suffer from another category. However, if one is managed to classify them broadly into three basic classes and then deploy different machine learning algorithms as per their class, accuracy will definitely increase. So this research presents an algorithm to classify between R-DGA, W-DGA and mixed DGA.

3 PROPOSED FRAMEWORK

Victim of a DGA based malware initiates the DNS requests at a high rate. The response to most of these DNS requests is NX domain, which is the key characteristic of DGA malware, thus incorporating it in the proposed algorithm. As shown in the figure 2 the proposed algorithm has two main modules live network monitoring and DGA classification which are discussed below.

3.1 Live Network Monitoring

The main characteristic of DGA malware is their network activity. Most commonly such malware checks the availability of internet by sending UDP packets to some renowned websites like google, yahoo, facebook etc. In addition, sometimes they also need to read their seeds form online sources, hard-codded in their binary files. Once the FQDN is created, they start sending the http requests for them. Most of such domain names are non existent and DNS resolver send NX domain response. To capture live DNS response we are using wire-shark tool and incorporated in Python. Every DNS response is captured, if its success full the system ignores it, if its unsuccessful the system go for packet inspection for error code.Error code 3 means its NX domain. In addition to the error code it also gives the source port, destination port, domain name for which the query name been initiated and many more.

3.2 DGA Classification

SLD is extracted from FQDN which in turn is extracted from the unsuccessful DNS query response . SLD, a sequence of alphabets, digits and special characters ($-$,_) without spaces, is tokenize into its constituent subwords via probabilistic model defined by Peter Norvig (Norvig, 2009). The model works on maximum likelihood estimation(MLE) which is determined via Bayes theorem.

The proposed technique is based on a statistical language model of unigrams, alongwith their occurrence frequency. The dataset comprising of unigrams and their frequency is taken from Google Corpus (Google, 2012). It contains almost 1 trillion tokens, but to keep the size manageable we only utilize the tokens having the frequency greater than 10000. Any token having the occurrence frequency less than 10000 is considered as unknown word. The unigrams are independent but their characters follow a particular sequence in a particular domain name, thus making a Bayesian network, an acyclic directed graph. HMM being a sequential classifier and a technique to encode the Bayesian network, is deployed to determine the probable word boundaries(Yan et al., 2021)in a SLD. HMM consists of observable states,

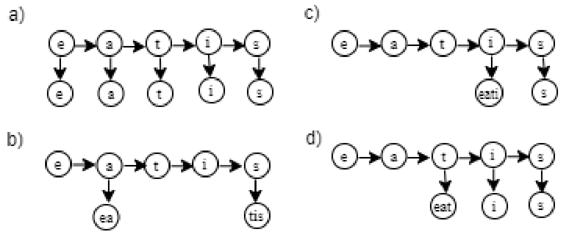


Figure 3: HMM.

hidden states, initial probabilities, transition probabilities and emission probabilities. Here, the observable states are the positional characters in the domain name, and the hidden states are the probable unigrams as shown in the figure 3. Here, in figure 3, the rightward arrow refers to the transition state and downward arrow refers to the hidden states. For example, if the given domain name is 'eatis', then the sample combinations are shown in the figure 3. These sample sets include { 'e','a','t','i','s' },{'ea', 'tis'}, {'eati','s'},{'eat','i','s'}. Probabilities of each set is determined using the relative frequency. Hidden states or the unigrams in a particular set are independent in nature, thus we can apply the chain rule as depicted in equation 1.

Mathematical notation of the chain rule is:

$$P(C_{1:n}) = \prod_{k=1:n} P(C_k) \tag{1}$$

which is also known as Naive Bayesian Assumption.

The algorithm determines all the probable unique sets of unigrams present in the SLD, compute their probabilities through the chain rule equation(1) and then using the Maximum Likelihood Estimation(MLE), given in equation 2 determines the most probable unigram boundaries within the SLD string.

$$P(C_{1:n}) = \underset{i}{argmax} P(c_i) \tag{2}$$

The unknown unigram must not have a zero probability but instead a lesser one as compared to the known unigram. So it is calculated via equation 3. Here, **P** depends on the length of unigram, so longer the length smaller its probability.

$$P(unk) = \frac{10}{N * 10^{length_{unk}}} \tag{3}$$

Another challenge is to deploy an efficient algorithm for determining the most probable segments or the subwords. The most common and the easiest technique is brute force ie computing the all possible sequences and selecting the one with the highest probability, thus having the exponential time complexity.

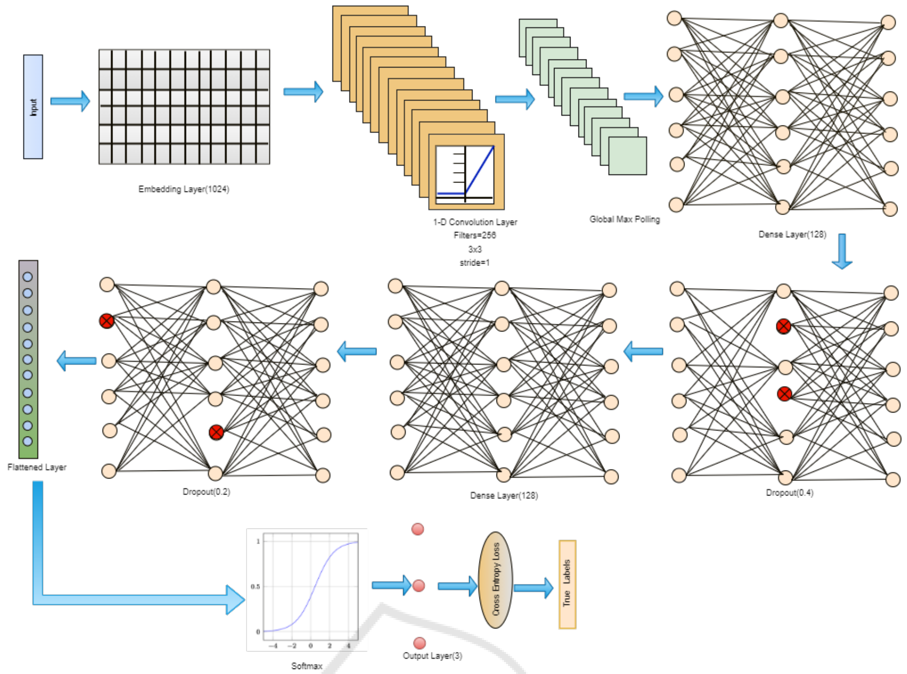


Figure 4: Machine Learning Framework.

To optimize the solution we have selected Viterbi algorithm (Ciaperoni et al., 2022), a dynamic programming technique. It reduces the time complexity by avoid redundant calculations. Its time complexity is linear in the length of the segment and quadratic in the number of possible segments. This makes it much more efficient than the brute force approach, especially for longer domain names with many possible segments.

3.3 Machine Learning Framework

Table 1: List of Features.

Features	Description
Probabilities of segments	Domain name is divided into probable segments based on their probabilities
Length of segments	Segments having small lengths have higher probabilities
Count of Segments	Total number of segments in a domain name
Ratio of digits	W-DGA has either 0 or 1 digits whereas R-DGA may have many digits depending upon its algorithm
Count of special Charatcers	Most of the samples belonging to W-DGA and Mixed DGA have special characters

The selected features, extracted from SLD, are summarized in table 1. There are DGA like ’abcbot’ which generates gibberish SLD with only 1 segment. On the other hand, ’NGIOWEB’ generates word based SLD, having as many as 14 subwords, including the special characters. The special characters are considered as a separate segment. However, digits, if exists any, may become the part of segment depending upon the probability. For example, consider a SLD ’9995bc0c’ generated by ’antavmu’ is a single segment having the probability 9.75E-20 computed from the equation 3. However, ’7286a423a16a13886a2511c8afa8df65’ is another SLD, a R-DGA generated by bamital. The algorithm divides it into 2 segments: ’7286a423a16a13886a2511c8’ and ’afa8df65’ having probability 9.75E-36 and 9.75E-20 respectively. It is evident from the above examples the probability decreases as the length of the segment increases. Now consider a ’Bigviktor’, a W-DGA, it generates domain like ’holdthenprofessional’. The proposed algorithm breaks it into ’hold’, ’then’, ’professional’ with 6.222E-5, 3.60E-4 and 1.2E-4 respective probabilities. Usually, the maximum length of a SLD is upto 64 characters and the maximum segments we found in more than 0.1 million samples are 14. But to handle a zero day DGA, the proposed algorithm has a cushion for 30 segments. As shown in the table 1, we are also considering the length of these segments. So, for 30 segments, there are 30 lengths. Missing segments and the lengths are considered are zero. In addition, total number of segments in a SLD, ratio of digits and special character is also included. All these features are used in fully connected neural net-

Table 2: Summary of Dataset.

Category	DGA	Samples	DGA	Samples	DGA	Samples
R-DGA	ABCBOT	27	ANTAVM	32	Bamital	104
	Chinad	1000	Conficker	494	Cryptolocker	1000
	Dicrypt	1000	Dmsniff	1000	Dyre	1000
	Emotet	5952	Enviserve	491	Flubot	30000
	Fobber	596	Gamevoer	12000	Gspy	100
	Locky	1178	Nymaim	481	Padcrypt	2279
	Necurs	40950	Qakbot	24804	Ramnit	20060
	blackhole	180	ccleaner	30	cooperstealer	18
	feodo	263	m0yv	63	madmax	530
	monerominer	2495	murofet	8560	mydoom	10037
	necro	2962	omexo	40	proslikefan	100
	pykspa	7930	qadars	2200	Ranybus	13302
	rovnix	4453	shifo	2541	shiotob	8004
	simda	12383	symmi	4256	tempedreve	2733
	tinba	13420	tinyuke	200	tofsee	20
	tordwm	500	vawtrak	845	vidro	100
	virut	9712	wauchos	5940	xshellghost	100
W-DGA	Bigviktor	1007	Matsnu	903	Suppobox	2303
Mixed	Ngioweb	5274	Banjori	7306	kfos	121

work (FCNN) and CNN. FCNN gave more than 92%, whereas CNN gave more than 99% accuracy, so we selected CNN for DGA classification. These results prove the strength of the selected features as both machine learning algorithms gives accuracy greater than 90%.

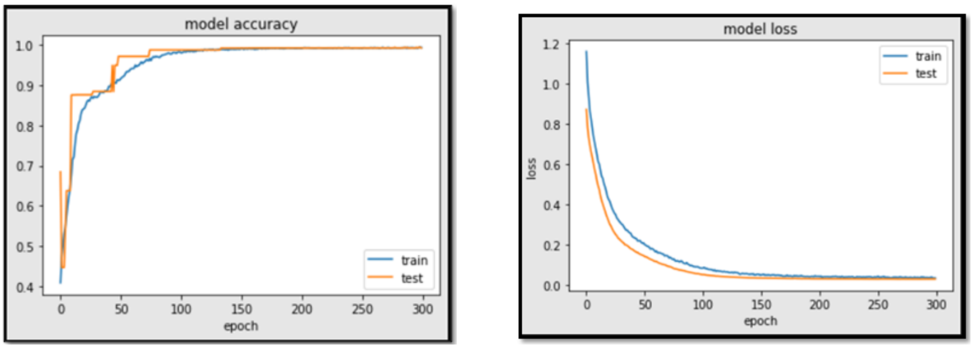
Length of feature vector may vary with the length of SLD. To normalize the feature set, zero padding is introduced, thus generating a sparse matrix. This sparse matrix becomes the input for a CNN. The sequential model of tensor flow is used and the arrangement of layers with their dimensions are depicted in figure 4. To convert the sparse matrix into a matrix having real values, embedding layer is deployed. The output of the embedding layer then becomes the input of the 1D convolution layer. Convolution layer has 256 filters of size 3x3, having the stride=1. Maximum Pooling layer is used here to select the features having the maximum values. Then comes the dense layer with 128 hidden units and relu activation function to handle the non linearity. In order to avoid overfitting, two dropout layers are added as shown in the figure 4. And the last dense layer has 3 hidden units having the softmax activation function for the multi class classification.

4 PERFORMANCE AND RESULTS

The proposed algorithm is trained and tested on Intel(R) Core(TM) i7-1165G7 CPU @ 2.80 GHz 2.803 GHz and 16 GB RAM.The dataset comprising of different 57 DGA families as listed in table 2, is used for training and testing. It is collected from Netlab (Netlab360, 2023), CIC dataset (for Cybersecurity (CIC), 2021) and kaggle (Kaggle, 2021) which are available online. In addition, we also executed the DGA algorithms which are available at github (Bader, 2023) and tested our algorithm on them. In total we incorporated almost 0.27 million domain names for training and testing. Almost 23% of the dataset is redundant, which is discarded and the remaining 0.21 million is used for training and testing. Out of 0.21 million domain names, 60% samples are selected randomly for training and the remaining 40% are used for testing. Training data is further divided into training and validation in the ratio of 60:40 respectively. The model is trained using 300 epochs and the its accuracy and loss are shown in the figure 5 (a) and (b) respectively.

Accuracy graph 5(a) shows that the model keeps on learning till 100 epoch and after that learning rate becomes stable. On the other hand 5(b) shows that loss decreases with the increase in number of epoch. Also the confusion matrix for the test data is plotted in the figure 6. The rows represents the true class and the column represents the predicted class. Here, label '0','1' and '2' represents R-DGA, W-DGA and Mixed DGA respectively. Confusion matrix shows that R-DGA has 100% accuracy as compared to the rest of the two. However, there are some missed classification in case of W-DGA and Mixed DGA. Although the overall accuracy is still greater than 99%.

After the training , then the complete system is tested against the DGA based malware, which are executed in VMware with customized settings. When the malware generates the DNS request, wireshark traces it and looks for NX domain. In case of NX domain, the domain name is passed to the proposed al-



(a) Accuracy (b) Loss

Figure 5: Accuracy and Loss.

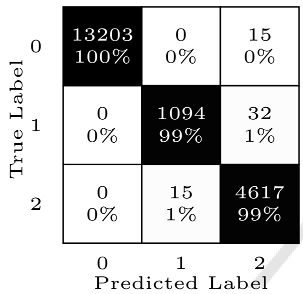


Figure 6: Confusion Matrix.

gorithm which then breaks it into its constituent parts and finally enters into machine learning framework for classification.

To optimize the solution in terms of time complexity and space complexity Viterbi algorithm(Cahyani and Vindiyanto, 2019) is used as it reduces the time complexity by using dynamic programming to avoid redundant calculations and considering only the most likely segment at each step.

5 CONCLUSION

DGAs are deployed to hide the malicious C2. DGAs may generate gibberish domain names and the sophisticated ones generate the dictionary oriented domain names or the combination of both, thus difficult to detect. Researchers have devised different techniques, usually based on humanly crafted features, to detect and classify such DGAs, but they are specific to one class only. This research proposes an algorithm to differentiate between the gibberish domain names, dictionary oriented domain names and Mixed ones. Now the researchers can deploy different machine learning techniques to each of these categories for better accuracy.

REFERENCES

Amini, P. (2008). Kraken botnet infiltration. Available at http://dvlabs.tippingpoint.com/blog/2008/04/28/kraken-botnet-infiltrationdvlabs.tippingpoint.com.

Antonakakis, M., April, T., Bailey, M., Bernhard, M., Bursztein, E., Cochran, J., Durumeric, Z., Halderman, J. A., Invernizzi, L., Kallitsis, M., et al. (2017). Understanding the mirai botnet. In *26th {USENIX} security symposium ({USENIX} Security 17)*, pages 1093–1110.

Atzeni, A., Diaz, F., Lopez, F., Marcelli, A., Sanchez, A., and Squillero, G. (2020). The rise of android banking trojans. *IEEE Potentials*, 39(3):13–18.

Bader, J. (2023). Reverse engineering of domain generation algorithms. Available at:https://github.com/baderj/domain_generation_algorithms.

Bisio, F., Saeli, S., Lombardo, P., Bernardi, D., Perotti, A., and Massa, D. (2017). Real-time behavioral dga detection through machine learning. In *2017 International Carnahan Conference on Security Technology (ICCST)*, pages 1–6. IEEE.

Bromium (2019). Emotet:a technical analysis of the destructive, polymorphic malware. Available at https://www.bromium.com/wp-content/uploads/2019/07/Bromium-Emotet-Technical-Analysis-Report.pdf.

Cahyani, D. E. and Vindiyanto, M. J. (2019). Indonesian part of speech tagging using hidden markov model–ngram & viterbi. In *2019 4th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE)*, pages 353–358. IEEE.

Ciaperoni, M., Gionis, A., Katsamanis, A., and Karras, P. (2022). Sieve: A space-efficient algorithm for viterbi decoding. In *Proceedings of the 2022 International Conference on Management of Data*, pages 1136–1145.

Erquiaga, M. J., Catania, C., and García, S. (2016). Detecting dga malware traffic through behavioral models. In *2016 IEEE Biennial Congress of Argentina (ARGENCON)*, pages 1–6. IEEE.

for Cybersecurity (CIC), C. I. (2021). Cic-bell-dns 2021 dataset. Availabe at : https://www.unb.ca/cic/datasets/dns-2021.html.

Google (2012). Corpus-n gram viewer. Available at: http://storage.googleapis.com/books/ngrams/books/datasetsv2.html.

Grill, M., Nikolaev, I., Valeros, V., and Rehak, M. (2015). Detecting dga malware using netflow. In *2015 IFIP/IEEE International Symposium on Integrated Network Management (IM)*, pages 1304–1309. IEEE.

Hwang, C., Kim, H., Lee, H., and Lee, T. (2020). Effective dga-domain detection and classification with textcnn and additional features. *Electronics*, 9(7):1070.

Internet, A. (2018). Alexa dataset. Available at https://www.alexa.com/topsites.

Kaggle (2021). Kaggle:domain generation algorithm dataset. Available at:https://www.kaggle.com/datasets/gtkcyber/dga-dataset.

Labs, K. (2017). Shadowpad: Popular server management software hit in supply chain attack. Available at https://media.kasperskycontenthub.com/wp-content/uploads/sites/43/2017/08/07172148/ShadowPad_technical_description_PDF.pdf.

Liu, Z., Zhang, Y., Chen, Y., Fan, X., and Dong, C. (2020). Detection of algorithmically generated domain names using the recurrent convolutional neural network with spatial pyramid pooling. *Entropy*, 22(9):1058.

Netlab360 (Accessed: May 19, 2023). Network security research lab at 360. https://data.netlab.360.com/dga/.

Norvig, P. (2009). *Natural Language Corpus Data:Beautiful Data*, pages 219–242. O'Reilly Media.

Oppenheim, M., Zuk, K., Meir, M., and Kessem, L. (2017). Qakbot banking trojan causes massive active directory lockouts. Available at https://securityintelligence.com/qakbot-banking-trojan-causes-massive-active-directory-lockouts/.

Pereira, M., Coleman, S., Yu, B., DeCock, M., and Nascimento, A. (2018). Dictionary extraction and detection of algorithmically generated domain names in passive dns traffic. In *International Symposium on Research in Attacks, Intrusions, and Defenses*, pages 295–314. Springer.

Ren, F., Jiang, Z., Wang, X., and Liu, J. (2020). A dga domain names detection modeling method based on integrating an attention mechanism and deep neural network. *Cybersecurity*, 3(1):1–13.

Shahzad, H., Sattar, A. R., and Skandaraniyam, J. (2021). Dga domain detection using deep learning. In *2021 IEEE 5th International Conference on Cryptography, Security and Privacy (CSP)*, pages 139–143. IEEE.

Skansi, S. (2018). Autoencoders. In *Introduction to Deep Learning*, pages 153–163. Springer.

Technologies, C. P. S. (2020). July's most wanted malware: Emotet strikes again after five-month absence. Available at https://blog.checkpoint.com/2020/08/07/julys-most-wanted-malware-emotet-strikes-again-after-five-month-absence/.

Tian, S., Fang, C., Liu, J., and Lei, Z. (2016). Detecting malicious domains by massive dns traffic data analysis. In *2016 8th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC)*, volume 1, pages 130–133. IEEE.

Vinayakumar, R., Alazab, M., Srinivasan, S., Pham, Q.-V., Padannayil, S. B., and Simran, K. (2020). A visualized botnet detection system based deep learning for the internet of things networks of smart cities. *IEEE Transactions on Industry Applications*, 56:4436–4456.

Vormayr, G., Zseby, T., and Fabini, J. (2017). Botnet communication patterns. *IEEE Communications Surveys Tutorials*, 19(4):2768–2796.

Wang, T., Lin, H., Cheng, W., and Chen, C. (2017). Dbod: Clustering and detecting dga-based botnets using dns traffic analysis. *Computers and Security*, 64:1–15.

Wang, Z., Jia, Z., and Zhang, B. (2018). A detection scheme for dga domain names based on svm. In *Proceedings of the 2018 international conference on Mathematics, Modelling, Simulation and Algorithms (MMSA 2018). Atlantis Press*.

Xu, C., Shen, J., and Du, X. (2019). Detection method of domain names generated by dgas based on semantic representation and deep neural network. *Computers& Security*, 85:77–88. https://www.sciencedirect.com/science/article/pii/S0167404818312938.

Yan, F., Liu, J., Gu, L., and Chen, Z. (2020). A semi-supervised learning scheme to detect unknown dga domain names based on graph analysis. In *2020 IEEE 19th International Conference on Trust, Security and Privacy in Computing and Communications (TrustCom)*, pages 1578–1583. IEEE.

Yan, X., Xiong, X., Cheng, X., Huang, Y., Zhu, H., and Hu, F. (2021). Hmm-bimm: Hidden markov model-based word segmentation via improved bi-directional maximal matching algorithm. *Computers & Electrical Engineering*, 94:107354.

Zhao, H., Chang, Z., Bao, G., and Zeng, X. (2019). Malicious domain names detection algorithm based on n-gram. *Journal of Computer Networks and Communications*, 2019.