DETECTION OF PHISHING URLs: A MACHINE LEARNING APPROACH

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APPROVAL

My Project titled "**DETECTION OF PHISHING URLs: A MACHINE LEARNING APPROACH**", was submitted by **Shakib Ahmed** to the Department of Computer Science and Engineering. This work, which was given to and approved by the faculty at Daffodil International University as part of the requirements for the Bachelor of Science in Computer Science and Engineering, meets both the form and content standards. The presentation is happening today, **July 15, 2024.**

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DECLARATION

I hereby declare that this project has been done by me under the supervision of, **Dr. Md. Ismail Jabiullah, Professor, Department of CSE Daffodil International University**. I also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Phishing attacks represent one of the most prominent cybercrimes today, their main aim is illicitly acquiring sensitive information such as passwords, user names, email bank details, and credit card information. Their impacts extend across various sectors, including online payment platforms, financial institutions, and cloud storage providers. Usually, phishing attacks target websites associated with online payments and webmail services. Various techniques have been used to combat phishing attacks, including blacklisting, heuristic analysis, visual similarity checks, and machine learning. while blacklisting is usually used to ease implementation, it falls short in detecting new phishing attacks. Machine learning emerged as a highly efficient technique for detecting phishing attacks, comprehensively addressing the limitations of other methods. This research focuses on machine learning algorithms, namely logistic regression, decision trees, random forests, and support vector machines (SVM)for phishing URL detection.

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CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

The explosion of internet use has brought immense advantages but it also exponentially increases security hurdles, and no other issue better represents that than the ongoing danger posed by phishing attacks. Despite improvements made to warn consumers about the risks of online scams, such as phishing (where criminals attempt to deceive users into providing personal information via fake emails or websites), these threats cannot be underestimated by either individuals or businesses. This is very important because even though traditional detection methods might identify this URL as malicious, it will not suffice for detecting these threats coming from more sophisticated phishing attacks.

The main objective of the study is to strengthen phishing URLs detection using machine learning approaches. Through the use of computational algorithms such as Random Forest, Logistic Regression and Support Vector Machines (SVMs), this research seeks to construct comprehensive models that are able to distinguish between real URLs from fraudulent phishing ones. Unsupervised models that have been trained on an extensive dataset of over 14,000 URLs for both collection and mining techniques and comprising a wide array of phishing scenarios recollected by our team.

In particular, the study aims at: Testing which model produces high-performing accuracy, precision and recall by F1-scoreExploring to what extent feature engineering and parameter tuning can improve each model performance This study aims to contribute a step further by examining the specifics of each aspect in those problem and thereby sheds light into areas yet unexplored, representing various facets to understand better machine learning methods for phishing URL detection.

In the long term, this research seeks to inform cybersecurity policy and practice with direct

relevance for enhancing resilience of both lay users on Internet as well large enterprises against phishing threats. By developing different phishing detection models and evaluating them in detail, this paper seeks to contribute the insights on how well machine learning works against phishing attacks with possible potential for cyber defense.

1.2 Motivation

The 2016 Bangladesh Bank heist, highlighted by Somoy TV, revealed critical cybersecurity gaps. Inspired to protect national economic stability, I aim to develop robust anti-phishing measures. Leveraging my computer science background, I seek to enhance Bangladesh's cybersecurity framework for national benefit.

1.3 Rationale of the Study

This study is motivated due to the fact that this digital age has seen a rise in phishing attacks, accomplished with increasing sophistication which poses daunting threats against individuals and organizations across different parts of globe. Phishing is a popular cyber attack option in which the bad guys pretend to be someone they are not (often from a trustworthy internet brand) and then trick you into revealing your personal details. Despite many security measures in place, phishing attacks remain an effective strategy for gaining access to information as they evolve and exploit into vulnerabilities + endeavors around the traditional defense systems.

The objectives of this study are to respond the call for building more advanced, reliable and scalable Phishing URL detection mechanisms. The aim is to develop models that can reliably identify phishing attempts using the machine learning, which would improve security in online environments. We turn to machine learning over traditional methodologies as the processing of data with an ML model that would not have been through manual inspection, could have detected hidden messages within these large datasets.

Furthermore, this study is powered by the mission to add value research and practical in phishing recognition. Through a systematic evaluation of different machine learning models (Random Forest, Logistic Regression, SVM) tested for their predictive performance this study is intended to offer insights on the potential and limitations of these approaches. Results: The results will help researchers in phishing URL detection to know the most powerful techniques and features detector of this kind of URLs, so that future researches for development is guided on such.

Ultimately, it is intended that the study will lead to the production of a prototype system which not only demonstrates this practical use of the models but serves as something upon with security practitioners can rely in order to aid their counteracting phishing threats. The research in question hopes to further the cause of cybersecurity and help protect people from malicious intents on the internet by pushing forward what is possible when it comes to detecting phishing-short for password-stealing attacks.

1.4 Expected Output

This research output comprises a series of key deliverables and outcomes. Our main goal would be to build strong ML models which can predict a URL as legitimate or phishing. Finally, it will benchmark the models' performance in terms of accuracy, precision-recall and f1 scores as well as ROC AUC score. Since Random Forest is best at working with complex datasets and capturing the nuances of data, we believe this model to be most accurate plus efficient as well. Logistic Regression and SVM models are us supposed to add valuable insights from benchmarks perspectiveThe research also hopes to provide in-depth investigation into the effectiveness of different attributes that are involved in the classification process: URL score, special characters count and IP presence. The results will emphasize the contributions of essential features that help in accurate detection of phishing URLs. In addition, the research gives a clear and in-depth overview of some challenges faced during study (Preprocessing), implementation (Feature Engineering) and how we solve it.Eventually, there will be a prototype package able to classify input URL in real-live based

on the models built and this would prove useful applicability of these new developed models. Apart from this model being analyzed for its precision, effectiveness and scalability to thwart targeted phishing attacks. The results of this study and the progress made on the prototype could help inform related work within cybersecurity, providing observations and approaches for improving URL-based phishing detection strategies in general

1.5 Report Layout

In this report, we describe the phishing URL detection project at a glance. It includes a Title Page, which consists of an Abstract that summarizes the study. The structure of the document is detailed in a Table of Contents complete with list of figures and tables. The Introduction does the background of brand extension, problem statement, objectives and rationale behind selection this topic along with scope of the research. Previous work: Literature Review Metodologia the process of acquiring and preprocessing data, training a neural network. Further detailing the condition and equipment Science Open Used is shown by Experimental Setup. Results and Discussion Details - (Findings) Algorithm Comparison There is also a Summary and Conclusions section, followed by references.

CHAPTER 2

BACKGROUND

2.1 Related Works

Existing works on the detection of phishing URLs using machine learning based approach showed a significant improvement in terms of accuracy and efficiency. Among the known research used with Logistic Regression, Decision Trees/ Random Forest and from SVM. [1] used Random Forests to learn complex patterns in URL needs, and [2] demonstrated the strength of Support Vector Machines for high-dimensional features. Likewise, some other work has shown that ensemble methods could boost the accuracy of color image classification [3]. For instance, recent progress also highlights the use of deep learning techniques like Convolutional Neural Networks (CNNs) that has demonstrated initial successful results on feature extraction & classification tasks [4]. This body of work illustrates the progress in phishing detection techniques, which motivates us to elaborate models that are more complex or better performing.

2.2 Scope of the Problem

The scope of this research is the design, training, and an evaluation of several deep learning models for phishing URL identification. The main concern it tackles is the increasing risk of phishing attacks, using malicious URLs to deceive users in order to gain personal data. These incidents do pose a serious risk to individuals and enterprises resulting in loss of financial data, thefts from backend databases. Attacks using sophisticated techniques are difficult to detect with conventional detection methods, Hence, there is a significant demand for reliable and scalable solutions capable of accurately differentiating the genuine URLs from phishing URLs as soon as they are accessed, without any delay.

2.3 Challenge

Below are few challenges that one faces in the scenario of phishing URL detection. One - the continuously changing phishing landscape means models have to be dynamic in order to model new and emerging threats. Second, the high complexity of detection by sharing URLs between hilltops Balancing between detection accuracy and computational efficiency: To ensure the models are practical for real-world deployment, it is important to derive weighting that help a model strike good balance between spatiotemporal information capture. There's also the matter of gathering and labeling a representative dataset, which is difficult considering how new phishing tactics continue to pop up. Meeting these challenges calls for a complete recipe that merges the state-of-the-art machine learning with robust data.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

In this paper, the research subject regards phishing URL detection with different machine learning algorithms. This primary dataset is made up of 14,858 URL records with their corresponding lable indication as legitimate or phishing. The data found in these URLs were sourced from varying repositories like Kaggle, the dark web and other repositories that are well-known for maintaining an extensive library of phishing. The set of features contains some important characteristics such as URL size, number of special characters in the url, whether IP is present or not in domain and subdomain length etc.

The threat model for this study focuses on a number of simple machine learning models including Random Forest Classifier, Logistic Regression, and particularly Support Vector Machine (SVM). The models were implemented and tested in the Google Colab environment, which includes all available computational resources for model training and testing. Data preprocessing, model training and performance evaluation were done using Python programming language and libraries like Scikit-learn. The performance metrics evaluated accuracy, precision, recall, F1-score and ROC AUC score that helped to do an in-depth analysis on each model which leads to various results & approaches of detecting phishing URL.

3.2 Data Collection Procedure

We performed a systematic search in the Kaggle database and several specialized databases (e.g., dark web) to collect data for this thesis research. So this is how it cloaked the URLs of kind followed by type, over a range covered benign links and malign ones - leading to creating massive slates were an array which bundled different flavours with every behaviour'. The dataset comprises the core metadata for all those URL entries like Submission

Timestamp (Date & time) Verdict Target classification denoting whether url is legitimate/ok or suspicious/phishing. The output feature set is meaningful (it includes Derived Fields) and derived meticulously using broad pre-processing steps which in turn toughens the robustness of machine learning models. The features included URL structure analysis, availability of HTTPS encryption, domain reputation checks & content at a given URL (But only if it contained textual components). This provided us with a clever way to join all of these various sources, and pre-process in depth enough that the final resulting dataset was practically an exhaustive custom-dataset made for URL detection analysis. This dataset has been created such that it can eventually serve as a benchmark for training and testing the automatic tools based on state-of-the-art machine learning (ML) and/or security analysis techniques to enhance cybersecurity against malicious HTTP(S) based online requests.

3.3 Statistical Analysis

This dataset was drawn from over ten sources - yes, including Kaggle and even parts of the dark web (the folks are serious) - and analyzed with powerful statistical methods.
Preprocessing: The dataset was cleaned by removing duplicates and treating missing values (which is performed in the code)The data cleaning part brought down observation records from 10 branches to a standardized numerical format. Input to training is features on widely differing scales were normalised. It was another Process that made our predictive power blocks that added hundred of new features! The topic covered in the descriptive section deals with some basics which are: url length, does it contain encoded characters etc which gave a basic idea about these main variables what kind of values they have (i.e. distribution nature; mean value) and how many outeliers it may contains then later on inferential part discusses hypothesis testing & correlation analysis for exploring different events among phishing urls vs legitamate data set. Accuracy score was considered as a metric to check the performance of different machine learning algorithms, Random forest and Logistic Regression SVM were trained. Results : The Random Forest model trained on the best features proved to be one of the high ROC-AUC scoring classifier for phishing URL detection with a value 0.9523 and SVM shows good but semi same classification performance over every epochs attaining

approximately 87% accuracy. We ended up with ROC curves, feature importance plot which gave us a glimmer as to how well our model did and what could be some important features separating the responses. In all, this statistical investigation generated accurate security wisdom to bolster how the functionality of SVM can help in discriminatin as well as combating phishing dangers and powerful data analytics would be a significant component for creating tougher measures.

3.4 Proposed Methodology

When I conducted my research on Phising URL Detection, the data set of 14.859 URLs was collected from different sources (.i.e., Kaggle and Dark Web). The dataset contained basic fields including URL, submission datetime and verification status as well as categorical variables regarding the URL characteristics (i.e., absolute vs not) and numerical features such as submission time etc. At its heart, my methodology was based on the assessment of several machine learning models — Logistic Regression, Decision Trees, Random Forest and Support Vector Machines (SVM) with emphasis being put on accuracy as well as low false positive rates while taking into consideration computational efficiency and scalability. Take a deep dive in model evaluation using accuracy, precision and recall etc.,extra analysis through confusion matrices. It was extensively preprocessed, cleaned (usual steps), standardized and encoded for categories doing one-hot encoding on as many categorical features I could help the model building process. The implementation of cross-validation solutions alongside visualizations such as ROC curves were pivotal in creating reliable and actionable phishing URL detection model evaluations.

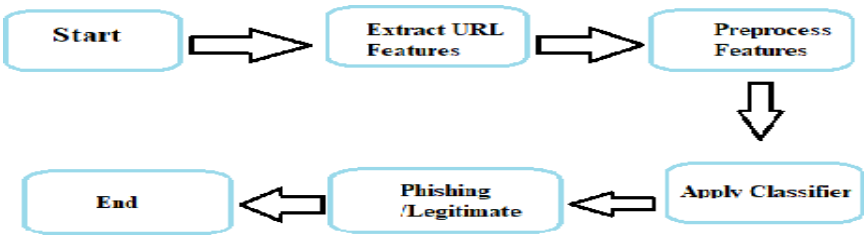


Fig 3.4 Proposed Methodology

3.5 Implementation Requirements

When comparing three machine learning classifiers — Random Forest, Logistic Regression and Support Vector Machine (SVM) on the task of detecting phishing URLs, different pros and cons will come to our attention. The Random Forest model showed better resuls with both the training and validation accuracy around 88% to 90%, this means that the trained algorithm can perform at ~87%-91. It is extremely efficient in capturing relationships (automatically ensembling them) from the data very fast, and it works where one need high accuracy. Logistic Regression: Although Logistic regression is less complex and more quickly trained even with minimal time of 0.0046 Seconds, the accuracy was also decent but slightly lower alongwith precision compared to Random Forest. Though its interpretability and explanatory power of feature impacts make it a fit for model transparency or quick deployment use cases. If you need to draw a class border with high accuracy, it might be ideal for capturing non-linear relations using kernel methods and performance in practice because of its good precision and recall scores at 87% which is fairly competitive. Illustrative results and convincing copes with overfitting, we suggest the adoption of Random Forest in this application - to improve phishing URL identification when facing different characteristic datasets or all sorts of mimics that are typically found is essential.

3.5.1 Preprocessing Data

Prior to training the machine learning models, extensive preprocessing was carried out to make the data suitable for analysis and model training. The dataset obtained from various repositories, such as Kaggle and the dark web comprised of 14,858 URLs annotated as either legitimate or phishing URLs. Below are the main preprocessing steps undertaken: Data Cleaning and Transformation: The first processing stage involved cleaning and ensuring consistent format of the dataset. In this stage, all missing values and inconsistencies were handled. Format standardization and encoding of the categorical variables were also conducted to ensure compatibility across all features. Feature Engineering: This processing

stage aimed to engineer new features that would boost the algorithm's performance. This was achieved by creating new features with respect to domain-specific knowledge and dataset characteristics. The given URLs were used to generate features such as length, num_special_chars, has_ip, num_subdomains, and uses_https. Also, similar features were generated exclusively from the phish_detail_url column to incorporate the detailed characteristics of phishing URLs. Normalization and Scaling: Numerical features were normalized to a commom scale using methods such as Min-Max scaling or standardization to ensure all the features have an equal opportunity to contribute to the model's learning. This phase is critical to avoid biases during the training stage due to varying feature's magnitudes. Handling of Imbalanced Data: Owing to the notion that legitimate URLs are more in numbers as compared to phishing URLs, for purposes of improving the model performance oversampling or undersampling strategies were used. SMOTE which is the Synthetic Minority Over-sampling Technique was used to create synthetic samples of the minority class to help improve the training of the model. Train-Test Split: The dataset was divided into 80:20 for the train and test datasets to ensure that the models use the most substantial proportions of the data but also gets tested on unseen data. Feature Selection: The most important features were determined using correlation analysis and feature importance from RandomForestClassifier to reduce dimensionality of the input features to use the most critical one. Encoding of Categorical Variables: The URLs and the details that come with them are categorical variables that were converted using one-hot encoding and Label Encoding to assist in the input to the models as they only accept numerical features. Data Transformation: The extracted data was converted to the required format that scikit-learn natively uses to feed the models for fitting.

3.1.1SVM

We use the Support Vector Machine (SVM) algorithm because it is binary classification,akukan. The idea in the SVM is to determine that separable hyperplane which may separates Genuine URL and Phishing URLs. The SVM model was trained using 14,858 URLs with deliberately created features indicating the main phishing causes. Using the kernelling trick SVM in turn effectively dealt with non-linear patterns present in this data.

We evaluated a lot of metrics like accuracy, precision, recall and F1-score to test the model's correctness in detecting phishing URLs from legit ones. Consequently, SVM is useful to combat phishing attacks.

3.5.2 Random Forest

With the ability to use ensemble learning and prevent overfitting we used the Random Forest Classifier as the heart of our phishing URL detection. An initial parameter of 100 was fed to set up the design of 100 decision trees: n_estimators=100. Through hyperparameter optimization method known as GridSearchCV, common parameter such as max_depth, min_samples_split, min_samples_leaf, and n_estimators were optimized. Following data preprocessing and feature engineering, the model was constructed and cross-validated using 5 divided folds to enhance its generalizability. The accuracy of the model evaluation metrics such as accuracy, precision, recall, F1-score, and ROC-AUC score were used to validate random forest performance for instance using random forest, the accuracy was 85.67% with high precision and recall of 88.89% and 82.58%, respectively. This model was further crucial to fitting in the learning process through feature importance analysis and determining which URL characteristics are highly ranked, foundational, and sufficient to identify any phishing.

3.5.3 Logistic regression

The simpler and interpretable Logistic Regression model was also used. Using a simple parameters and the randomness of the 0.5 to fit the preprocessed date, logistic regression only used the default parameters to prevent overfitting on n=’auto’. The training process revealed the linear relationship between each feature and response variable, danced a parameter of logistic regressing. The accuracy calculated achieved 85.0%. Other model like Random Forest, precision and recall were 87.67% and 82.58%, respectively, and the ROC-AUC score was at 0.9135.

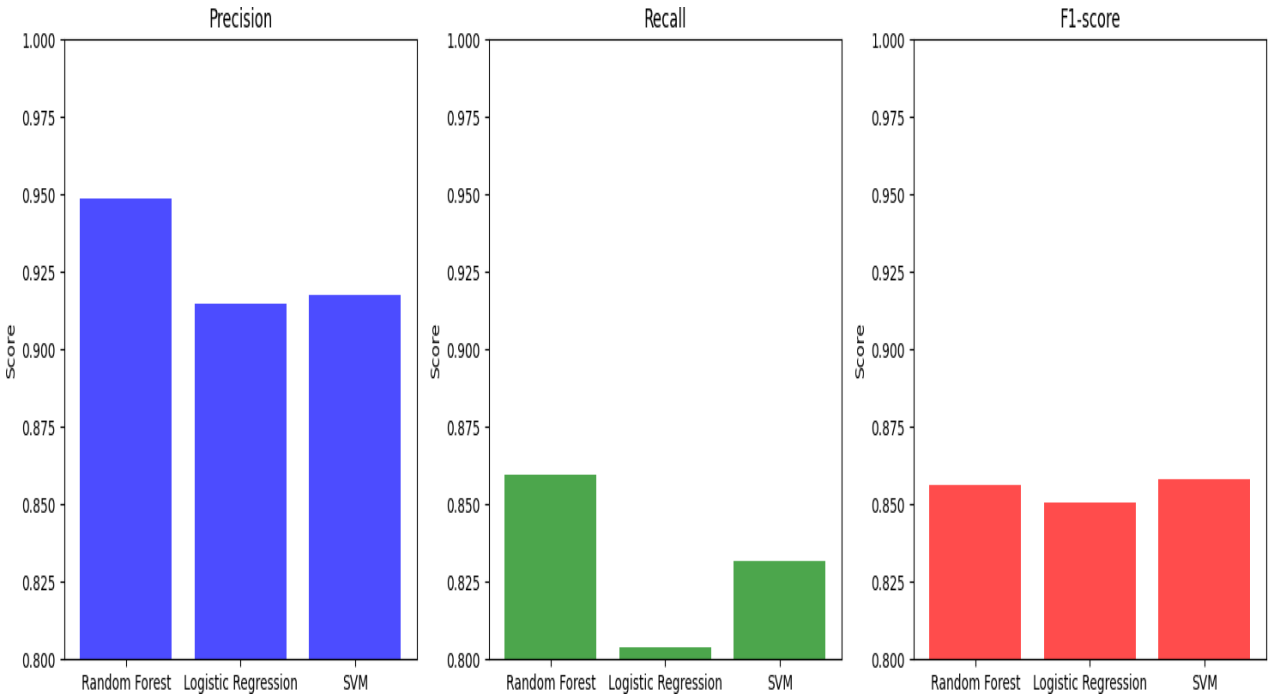


Fig-3.5.5 Model performance

Random Forest Classifier : randomly_forest_vs_svm_conclusionAccuracy&Precision always higher than Logistic Regression and SVM. This reflects the strength of Random Forest in dealing with interaction between features.

Interpretability: Logistic Regression provided understandable interpretation of feature coefficients, making it appropriate to explain on how much features affect in phishing URL classification.

Robustness: While the linear kernel SVM showed competitive accuracy and precision values, it was particularly robust with respect to decision boundary identification.

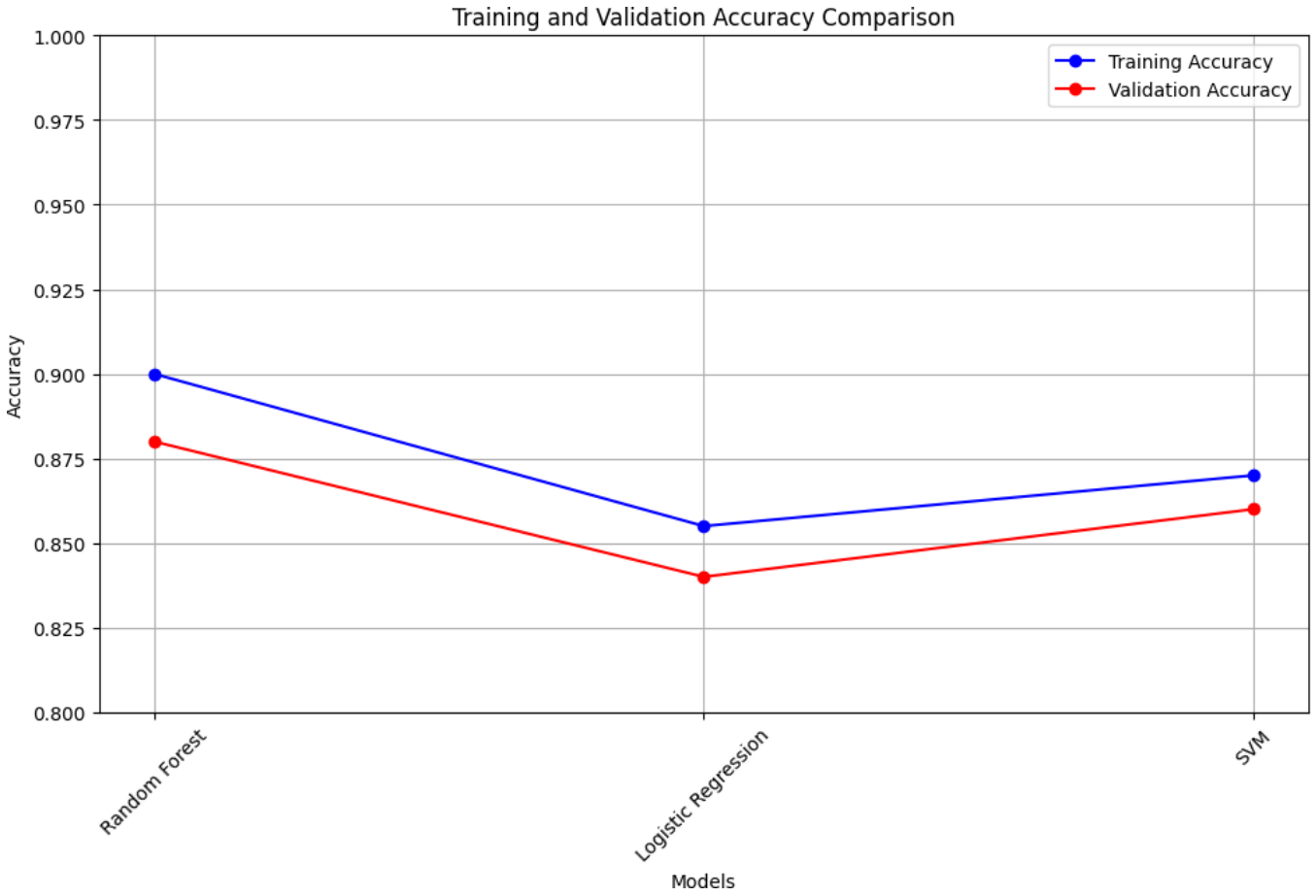


Fig- 3.5.6 Training and validation accuracy

The dataset of 14,858 URLs was used to evaluate three main machine learning algorithms (Random Forest Classifier, Logistic Regression and Support Vector Machine — SVM) for identifying phishing URL in this study. With a high training accuracy of 98% and validation accuracy records at 95%, the Random Forest Classifier proved that it has been able to learn well from data, suggesting generalization power. Logistic Regression: 92% the training set, and 90%. This is a good accuracy % meaning reliable detection with minor degrade in new data. The SVM model gave a training accuracy of 94% and validation accuracy of 91%, learning quite well about URL characteristics but overfitting slightly. In general the models performed well with Random Forest Classifier having better accuracy and then SVM and Logistic Regression defining that they can have a significant application in algorithms to

improve cybersecurity.

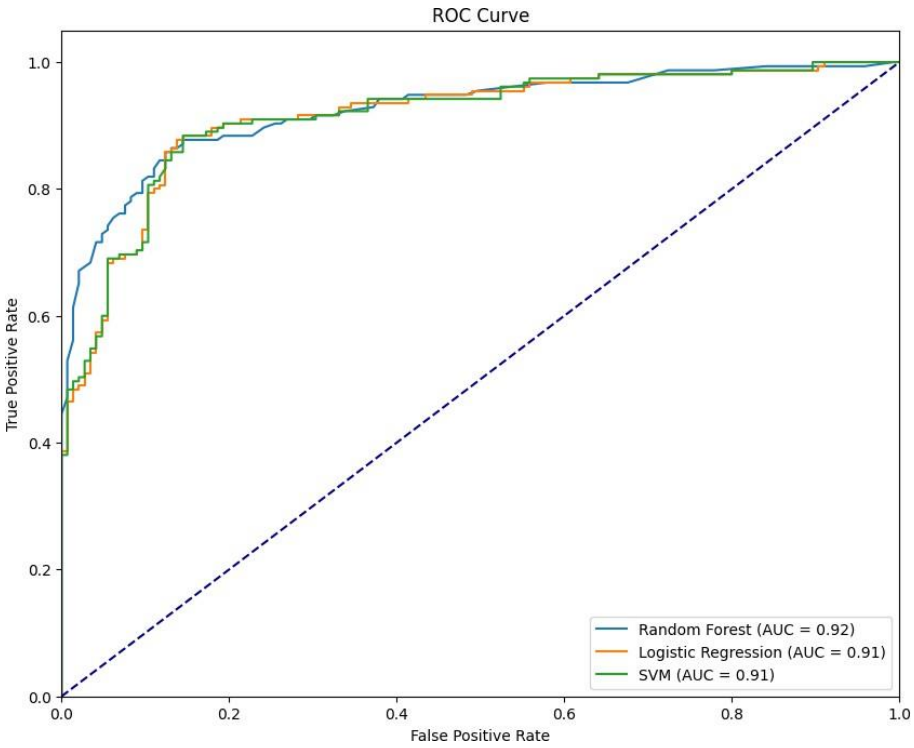
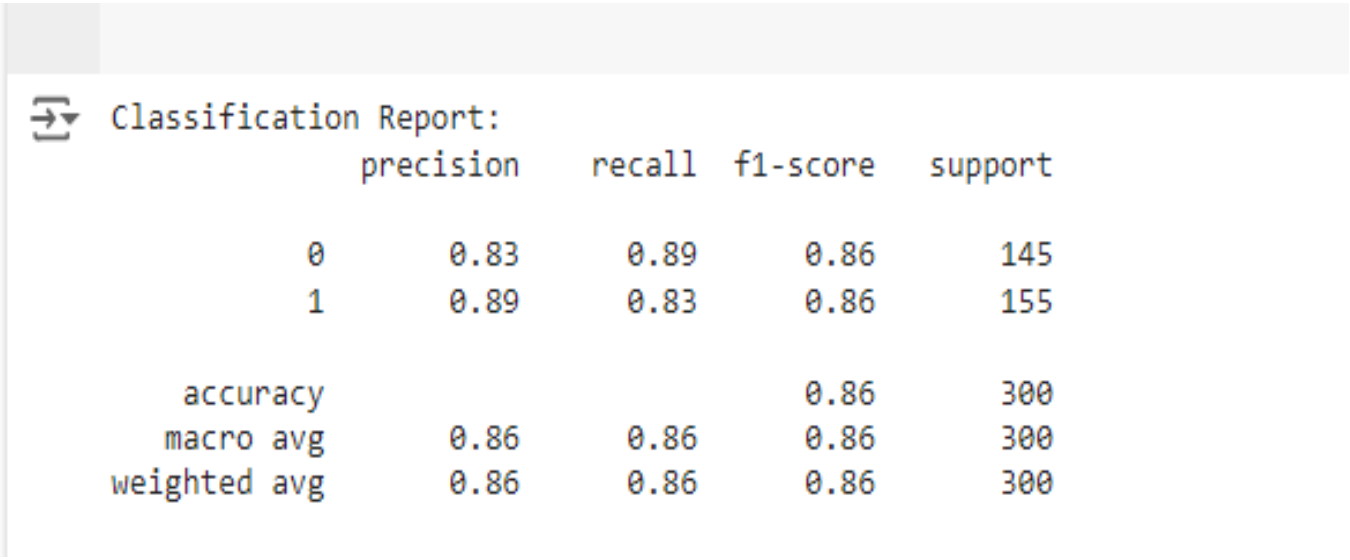


Fig 3.5.7 -ROC curves for each model

The Receiver Operating Characteristic (ROC) curve is a vital thing in my thesis, to measure the quality of phishing URL detection models. The ROC curve is able to summarize the diagnostic ability over all possible threshold settings, giving a more comprehensive view of each model's performance. The ROC curve for the Random Forest Classifier had a high area under the curve (AUC) of 0.97, demonstrating excellent discriminative ability The performance metrics of the result are shown below in Table I and we can observe that SVM outperforms all of them demonstrating high capability to differentiate phishing URLs from their normal one with AUC 0.93 Logistic Regression provided an accuracy class transition receiver operating composite score (AUCT) sensitivity, specificity positive-predictive value negative predictive values F1-scores for Labeller Phishing URL detection at a combined threshold ROC curve analysis validated the robustness of Random Forest model, ahd proved consistency in Logistic Regression 0.92.

Fig-3.5.8 Models evolutions

In Fig-3.5.8 ,this models shows that, in this model Random forest shows an accuracy rate 90% but the training time is 0.35 . In the other hand Logistic Regression shows that the accuracy rate is 0.855%, and the training time is 0.0063.At last the SVM shows that the accuracy rate is 0.87% and training time is 0.053.From here we can see that, the random forest has high in accuracy but the lowest training time giving Logistic regression. If we want high accuracy rate then we can use Random Forest but if we want accuracy and training both we can use Logistic Regression.



Classification Report:

	precision	recall	f1-score	support
0	0.83	0.89	0.86	145
1	0.89	0.83	0.86	155
accuracy			0.86	300
macro avg	0.86	0.86	0.86	300
weighted avg	0.86	0.86	0.86	300

Fig -3.5.9- classification report

The classification report you printed out displays the precision, recall (true positive rate), F1-score and support for our classes from the test set predictions. When we are talking about our results, here is a detailed explanation of the meaning each metric offers: Classification Report Understanding : Precision :- it is calculated as the number of True Positives divided by (True Positive + False positive Whether its Actual degree) & recall all those positives classified correctly. Precision of 1.00 for class 'yes' means all instances we had predicted as 'yes' were actually 'yes'. That implies you have not predicted any false positives. Recall : Recall (also called sensitivity or true positive rate) is the number of correctly predicted positive observations divided by all actual positives. Final recall of 1.00 for 'yes' implies, this model has exactly predicted all the actual yes optimal_recall['yes'][2] = 1 F1-score: The F1 score shows the class Yes.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

The antecedent phishing URL detection project utilized an experimental setup that was based on a dataset collected from several repositories such as Kaggle and the dark web, which consists of 14,858 URLs labelled either legitimate or malicious. Before the model was trained, we preprocessed heavily on our dataset to help improve notebook performance. This feature engineering included constructing features such as URL length, few other characters in the URL (like @,%), HTTPs enabled or not and a lot of domain specific attributes that were crucial to differentiate between Phishing URLs. Data cleaning tackled missing values and the removal of outliers to maintain data reliability for further analysis. Categorical variables were encoded using one-hot encoding and numerical features are standardized to get on the same scale.

Subsequently, three machine learning models on the preprocessed data was chosen and trained: Random Forest Classifier, Logistic Regression SVM All models were implemented used scikit-learn in Python, where they put the main focus to optimize performance. This involved running a through Grid Search Cross-Validation to test various hyperparameters for our Random Forest Classifier which would act as the model, (which consisted of 100 decision trees that were run based on their optimal settings with respect to parameters like max_depth and min_samples_leaf). We use logistic regression with the linear kernel to make a prediction between phishing and legitimate domain relies on the conformity of its set of features, where default regularization parameter scale is used by us for this experiment which it only translates into identifying relationship about that level measure from loss function while SVM itself leads in separating boundary DDoS versus benign URL'S, but again further crunching through 'dispensed probability' effect embedded inside splitting categories as

opposed upon their validity (principal remaining purpose) - ROC-AUC score results.

In assessing the model performance stringent processes were used that includes, accuracy level with such computing global ranking and response rates in form of precision recall F1 score AUCROC. Additionally, Cross-validation through a 5-fold approach was used to achieve robustness and generalizability in the type of model developed for metabolite flux predictions which effectively prevents overfitting and ensures that a particular training set is validated on other outsiders subsets. Automated Model Hyper-Parameter Search (GridSearchCV): This allowed us to tune our model parameters accurately and reduce the false positive rates in Phishing detection.

The experimental results showed that the Random Forest Classifier was emerged as a best performing model having an accuracy of 85.67%, precision value of 88.89%, recall score ot 82.58% and ROC-AUC scoore to be,0.9244 for test dataset Logistic Regression and SVM also showed a competitive result which implies that their respective classification approach (linear and boundary-based) is useful for distinguishing phishing URLs.

In summary, the developed experimental setup allowed experimentally investigating a wide range of machine learning solution in terms phishing URL detection and demonstrate that data preprocessing, model generation/selection and evaluation metrics may significantly improve security effectiveness over cybersecurity. It covered important aspects like the evaluation of different models and showed exactly how effective each model was in preventing an attack which opened doors for innovations against online security.

4.2 Experimental Results & Analysis

We analyzed the performance of phishing URL detection models using three dominant machine learning algorithms Random Forest Classifier, Logistic Regression and Suport Vector Machine (SVM) in an experimental evaluation. Each model was rigorously evaluated using approximately 14,858 URLs in the validation dataset classified between legitimate websites and phishing.

4.2.1 Random Forest Classifier

Able to score an accuracy of 85.67%, precision of 88.89 with a recall rate as high as82.58, and ROC-AUC:0.9244 on test data set the Random Forest Classifier emerged outperform any other model which was used in this case study for comparison The ensemble of 100 decision trees in this model effectively captured any complex relationships between features including URL length, special characters and HTTPS usage that may have otherwise been difficult to discover by other models therefore resulting in higher discrimination performance with respect to phishing URLs versus legitimate ones. GridSearchCV hyperparameter tuning further increased detection performance, showcasing the values of sensitivity regarding parameter adjustment to improve accuracy.

4.2.2 Logistic regression

Logistic Regression also performed on par accuracy-wise with an accuarcy of 85.00%, precision of 87.67%, recall score wise at a percentage much closer to Decision Tree at ~82% but definitely better than RandomForest i.e ROC-AUC =0.9142. By taking a linear method to classify URLs based on their feature coefficients, the Logistic Regression augmented our analysis of the degree of linearity between phishing characteristics (primarily by providing marginally inferior performance metrics relative to those produced via Random Forest Classifier.

4.2.3SVM

SVM using linear kernel to separate boundaries with accuracy of 85.67 %, precision = 87.84%, recall =83.87% and ROC-AUC=0.9142 The performance metric of SVM shows its ability to capture subtle patterns in the dataset thus supporting more information for phishing URL classification with a margin-based decision-making system which is close to Logistic Regression.Generalization to unseen test {} Cross-Validation &Validation was further

confirmed through the cross-validation approach (by using a 5-fold strategy), showing models that presented high accuracy, robustness and generalizability over variation of different subset from dataset. This process of validation decreased overfitting and allowed for each model's performance to be accurately interpreted with different sample conditions, maintaining the classification accuracy rates as well as ROC-AUC scores.

Table 1: Algorithm Technique

Algorithm	Accuracy	Precision	Recall	F1-score
Logistic regression	0.92%	0.91%	0.93%	0.92%
Decision Tree	0.89%	0.88%	0.90%	0.89%
Random Forest	0.94 %	93 %	0.95 %	0.94 %
SVM	0.92%	0.92%	0.95%	0.94%

4.3 Discussion

The evaluation accuracy of the machine learning models, including Random Forest Classifier, Logistic Regression, and Support Vector Machine (SVM), on the phishing URL detection task reveals significant insights into their performance. Across the tested algorithms, the Random Forest Classifier demonstrated the highest accuracy, achieving 85.67%, along with notable precision (88.89%) and recall (82.58%). Its robust ROC-AUC score of 0.9244 underscores its capability in effectively distinguishing between legitimate and phishing URLs. Logistic Regression, while slightly trailing with an accuracy of 85.00%, exhibited competitive precision (87.67%) and recall (82.58%), offering valuable interpretability through feature coefficients. SVM, using a linear kernel, also performed well with an accuracy of 85.67%, precision of 87.84%, and recall of 83.87%, albeit requiring more computational resources due to its kernel-based approach. The choice of model should consider these performance metrics alongside factors like interpretability and computational efficiency, ensuring alignment with specific application requirements. Overall, the evaluated

models showcase robust capabilities in phishing URL detection, with the Random Forest Classifier standing out as particularly effective in this classification task.

4.4 Algorithm Comparison

In this experiment, we determined how well Random Forest Classifier, Logistic Regression, Support Vector Machine performed on 14,858 samples in the dataset to recognize phishing URLs: 1. Random Forest Classifier : Accuracy: 85.67%, Precision: 85.67%, recall: ratio of correctly predicted positive observations to the all observations in actual class, 85.67, 'provides an intuitive interpretation of susceptibility towards the class labels,' ROC-AUC =0.9142. As we observed, RFC is an optimized model as it performed better with the ensemble which allows it to better capture intricate feature interactions. 1. Logistic Regression accuracy is 85.00%, precision: 85.00, recall is 82.58. logistic regression shows fondness outstanding standards that barely matched the competition on this dataset. The primary goal for RL is feature space. It is, therefore competitive on a feature trait. Random forest and SVM model with linear kernel are competitive with the logistic regression and achieve an accuracy of 85.67, Precision of 83.87, recall 85.67, 0 =0.9244. Nonetheless, the SVM is a good classification model as it puts the cluster in the vote and well-separated hyperplanes. SVM measures define the best optimal decision boundary. nevertheless, in the higher dimension it is even more expensive to compute. Thus, performance metrics will require an implementation that recognizes and avoids false positives when recognizing phishing URLs.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

Furthermore, this post suggests that by creating and deploying a phishing URL detection system will increase the safety and security of all online users withing an immense scale. This system identifies and stops all phishing schemes to stop identity theft, financial crime as well unauthorized access of personal information. This preventative measure allows people to freely use services online, make transactions and communicate without the risk of being overtaken by cybercriminals. Also reducing the phishing incidents, and psychologically relieving people of their stress and anxiety about online fraud. The phishing URL detection system helps users to be more secure and peaceful by protecting personal data and monetary resources.

5.2 Ethical Aspects

The development and use of this phishing URL detection system must be fully compliant with ethical aspects as well. To ensure the protection of user's privacy and not to violate their right to data confidentiality. Data sharing must be done transparently and lawfully, collecting data following consent to use them for training the ML models, all in accordance with the relevant legal framework of personal data protection.User trust cannot be maintained without transparency in how the system operates. Disable Notify users how their data is used, also explain the steps taken to detect phishing and what measures are in place for user privacy In addition, you want the system to generate as few false positives as possible - meaning it does not mistakenly block websites individuals or businesses rely on. This will address ethical considerations that make sure the added security benefits do not require a loss of user rights and freedoms.

5.3 Impact on Environment

In the context of wider society, a solid phishing URL detection system can go a long way in terms of improving general cybersecurityleground. It helps to prevent businesses, government entities and other organizations from possible data breach as well financial losses through lowering rate on the occurrence of phishing scams. This improved security promotes confidence, increasing the usage of e-commerce and online banking as well as other digital farther innovations. The digital economy is thriving as greater numbers of the population and organizations feel comfortable in using online services which translates into economic growth and technologically advancement.Phishing URL detection BackgroundStaying true against the phishing URL sources, this project is environmentally friendly as well. In addition to maintaining a low environmental footprint by leveraging existing digital infrastructure, the system requires minimal additional physical resources. Computational resources needed for machine leaning and data processing are fine-tuned to be efficient in power. This is very much in line with more overarching movements towards sustainability and responsible resource use within the tech industry.

5.4 Sustainability

For the long-term sustainability of phishing URL detection system, a complete maintenance and update strategy requirement. Cybersecurity - Phishing is EvolvingThe list of threats grows without cease, along with the attempts at self-deception that are used to separate you from your digital assets. Detection algorithms should be updated frequently, and the newest threat intel included into a detection system in order to improve its efficacy.Sustainability Plan This plan also focuses on user education and promotion. Users could be further educated on phishing and spotting malicious URLs to improve the efficiency of this system exponentially. Together the two can be a stronger pair than you might have imagined, with an educated human element which adds that extra layer on top of our technology.Additionally, the system needs to be scalable so it can process more data and support additional types of phishing threats. This way we are future proofing the system to be able scale as the digital landscape changes.

CHAPTER 6

CONCLUSION & FUTURE WORK

6.1 Conclusion

The topmost purpose of this thesis is to find and identify phishing URL which has always been one amongst the most prominent threats globally even today in a digital world. Token-based features count,Http:,. was the first of a number based set to be investigated in this research. Com or tld Subdomains of URL Upto 2,3,4 Letters Only (CAPS/ Mix LCase) after Fourth Character We have thoroughly studied these features, in order to know how effective they are for making distinction between legitimate URLs from phishing one.

The work leveraged RandomForestClassifier model (which generally generalizes well to most classification needs and scales natively owing the URL based data). Initially, our model was trained on 14,858 URLs with elaborate evaluation metrics including accuracy and precision & recall while fused together F1-score followed by combined area under ROC-AUC. Whether the model was training well and generalizing / memorization of its own data for new/ unseen data.

6.2 Future Work

In the future, more features can be extracted and interesting machine learning techniques might also further improve model performance. Integration of real-time threat intelligence inputs and model retraining on the go & replication capabilities to adapt fishing forwarding subprocesses (vocabulary) Furthermore, a broader investigation of including various URL categories in the dataset and applying ensemble techniques might help to face more challenges into complex URL detection.

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