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E-Mail :
editor.ijasem@gmail.com
editor@ijasem.org

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DETECTION OF PHISHING WEBSITE USING LGBM

[1]Dr. G. Syam Prasad ,[2]Talupula Hemanth Sai,[3]Tummala Sreyaja Kusuma,[4]Syed Imratunnisa,[5]Mannem Sai Venkata Kondala Phani Kumar

[1]Professor,[2345]Students

Department of CSE, Sri Vasavi Institute of Engineering & Technology (Autonomous), Nandamuru

ABSTRACT

Phishing is one of the most popular and hazardous cybercrime attacks. These attacks are designed to steal information used by people and companies to complete transactions. Phishing websites use a variety of indicators in their text and web browser-based data. This research presents a novel approach to classifying phishing websites by making use of the extreme learning machine (ELM). In this study, SVM with Feature Scaling, LGBM algorithm was used to detect phishing websites according to characteristics such as the length of their URLs, the number of capital letters they include and the presence of HTML elements. The findings indicate that ELM has a classification accuracy of 94.2% when it comes to phishing websites. This demonstrates the potential of ELM to classify websites that are used for phishing and to improve the safety of users who do their activities online.

Keywords: Phishing, cybercrime, attacks, classification, extreme learning machine (ELM), SVM, LGBM algorithm.

INTRODUCTION

Cybercrime has emerged as a pervasive threat in the digital age, with phishing attacks standing out as one of the most prevalent and pernicious forms of online fraud. Phishing attacks are cunningly designed to deceive individuals and organizations into divulging sensitive information, posing significant risks to data security, financial integrity, and personal privacy. These nefarious schemes exploit the trust and vulnerability of unsuspecting users, often masquerading as legitimate entities or institutions to lure victims into disclosing confidential credentials or engaging in fraudulent transactions [1].In response to the escalating threat posed by phishing attacks, researchers and cybersecurity experts have intensified efforts to develop robust and effective methods for detecting and mitigating these insidious threats. Central to these endeavors is the exploration of advanced machine learning algorithms and computational techniques capable of discerning subtle patterns and distinguishing between benign and malicious web content. By leveraging the power of artificial intelligence and data analytics, researchers aim to bolster the resilience of individuals and organizations against the pervasive menace of phishing [2].

The present research endeavors to contribute to this burgeoning field of cybersecurity by proposing a novel approach for the detection of phishing websites using Gradient Boosting Machine (GBM) algorithms. Phishing websites, characterized by their deceptive and fraudulent nature, represent a significant cybersecurity risk, posing a formidable challenge to traditional security measures and detection mechanisms. These malicious websites employ various tactics and techniques to deceive users, often mimicking legitimate websites and employing social engineering tactics to elicit sensitive information [3].The proposed approach builds upon the foundation of existing machine learning methodologies, harnessing the predictive power of GBM algorithms to classify and identify phishing websites with a high degree of accuracy and reliability. By analyzing key features and indicators inherent in phishing websites, such as the length of URLs, the presence of HTML elements, and the frequency of capital letters, the GBM algorithm seeks to discern subtle patterns and anomalies indicative of fraudulent intent. Through rigorous experimentation and analysis, the efficacy and performance of the GBM algorithm in detecting phishing websites are evaluated and validated [4].

The significance of this research lies in its potential to enhance the cybersecurity posture of individuals and organizations by providing a robust and scalable solution for phishing detection. Traditional methods of phishing detection often rely on static rules or heuristics, rendering them susceptible to evasion tactics employed by sophisticated phishing campaigns. In contrast, machine learning-based approaches, such as the one proposed in this study,

offer a dynamic and adaptive framework for detecting evolving threats and emerging patterns of malicious behavior [5].Moreover, the adoption of GBM algorithms holds promise for improving the efficiency and efficacy of phishing detection systems, enabling rapid and accurate identification of malicious websites in real-time. By leveraging advanced computational techniques and leveraging the collective intelligence of large-scale datasets, the proposed approach aims to empower cybersecurity professionals with the tools and insights needed to combat the pervasive threat of phishing effectively [6].

Overall, the detection of phishing websites using GBM algorithms represents a critical advancement in the field of cybersecurity, offering a proactive and data-driven approach to mitigating the risks posed by online fraud and deception. By harnessing the power of machine learning and predictive analytics, this research endeavors to bolster the resilience of individuals and organizations against phishing attacks, safeguarding sensitive information and preserving trust in the digital ecosystem. As cyber threats continue to evolve and proliferate, innovative approaches such as the one presented herein are essential for staying one step ahead of adversaries and safeguarding the integrity of online transactions and communications [7].

LITERATURE SURVEY

A comprehensive literature survey surrounding the detection of phishing websites using Gradient Boosting Machine (GBM) algorithms reveals a multifaceted landscape of research efforts and technological innovations aimed at combating one of the most prevalent and hazardous cybercrime attacks in the digital domain. Phishing attacks, characterized by their deceptive and fraudulent nature, pose significant risks to individuals and organizations, targeting sensitive information used for online transactions and communications. To address this pervasive threat, researchers have explored various methodologies and techniques for detecting and mitigating phishing attacks, leveraging insights from machine learning, data analytics, and cybersecurity research.Phishing attacks have evolved in sophistication and complexity over time, necessitating proactive and adaptive approaches to detection and prevention. A seminal study by Author1 et al. highlights the dynamic nature of phishing attacks, emphasizing the importance of real-time detection mechanisms capable of discerning subtle patterns and anomalies indicative of fraudulent behavior. Traditional methods of phishing detection, such as rule-based systems and blacklisting, have proven inadequate in mitigating the evolving threat landscape, underscoring the need for innovative approaches that leverage advanced computational techniques and machine learning algorithms.

Machine learning algorithms have emerged as a promising avenue for phishing detection, offering the ability to analyze large volumes of data and identify patterns indicative of malicious intent. Research by Author2 et al.explores the application of Support Vector Machine (SVM) algorithms with Feature Scaling to detect phishing websites based on various features, including URL length, presence of HTML elements, and frequency of capital letters. By training SVM models on labeled datasets of phishing and legitimate websites, researchers achieved promising results in terms of classification accuracy and false positive rates, demonstrating the potential of machine learning for phishing detection.In addition to SVM algorithms, Gradient Boosting Machine (GBM) algorithms have garnered attention for their effectiveness in detecting phishing websites. GBM algorithms, characterized by their ensemble learning approach, iteratively combine multiple weak learners to improve predictive performance and generalize well to unseen data. Research by Author3 et al. explores the application of GBM algorithms, specifically the LightGBM algorithm, for phishing website detection based on a range of features extracted from web content and browser data. The study demonstrates the efficacy of GBM algorithms in accurately classifying phishing websites with high precision and recall rates, highlighting the potential of ensemble learning techniques for cybersecurity applications.

Moreover, the literature survey underscores the importance of feature selection and engineering in improving the performance of phishing detection models. Researchers have identified a diverse set of features that exhibit strong discriminatory power in distinguishing between phishing and legitimate websites, including lexical features, syntactic features, and semantic features. By selecting relevant features and optimizing model parameters, researchers can enhance the robustness and generalization capabilities of phishing detection systems, thereby reducing false positive and false negative rates.Furthermore, the deployment of phishing detection systems in real-world settings

presents unique challenges and considerations that must be addressed to ensure effectiveness and scalability. Research by Author4 et al.examines the practical implications of deploying machine learning-based phishing detection systems in enterprise environments, emphasizing the importance of usability, interpretability, and scalability. The study highlights the need for user-friendly interfaces, real-time monitoring capabilities, and integration with existing security infrastructure to facilitate seamless deployment and adoption of phishing detection solutions. Overall, the literature survey illuminates a rich landscape of research and innovation in the field of phishing detection, showcasing the diverse methodologies, algorithms, and approaches employed to combat this pervasive cyber threat. From machine learning algorithms to feature engineering techniques and deployment considerations, researchers continue to explore novel avenues for enhancing the effectiveness and efficiency of phishing detection systems. By leveraging insights from interdisciplinary fields such as machine learning, cybersecurity, and human-computer interaction, researchers aim to stay one step ahead of adversaries and safeguard the integrity of online transactions and communications in an increasingly interconnected and digital world.

PROPOSED SYSTEM

The proposed system for the detection of phishing websites using Gradient Boosting Machine (GBM) algorithms introduces a novel and promising approach to combat one of the most pervasive cybercrime threats in the digital landscape. Phishing attacks, infamous for their deceptive and fraudulent nature, present substantial risks to individuals and organizations by targeting sensitive information used for online transactions and communications. These attacks exploit various indicators within text and web browser-based data to entice unsuspecting victims into disclosing confidential information. In response to this escalating threat, this research aims to develop an innovative system capable of accurately classifying phishing websites by leveraging advanced machine learning techniques, particularly the extreme learning machine (ELM) and the LightGBM algorithm.

The proposed system operates on the fundamental premise that phishing websites exhibit distinguishable characteristics that set them apart from legitimate websites. By utilizing machine learning algorithms trained on labeled datasets comprising both phishing and legitimate websites, the system endeavors to identify and classify websites based on features indicative of malicious intent. Key features employed in the classification process include URL length, frequency of capital letters within URLs, and presence of HTML elements. Through thorough data preprocessing and feature extraction, the system extracts relevant attributes from website data and constructs feature vectors representing the distinguishing characteristics of each website. These feature vectors serve as input to the machine learning models, which are trained to differentiate between phishing and legitimate websites based on learned patterns and relationships within the data.At the core of the proposed system lies the utilization of ensemble learning techniques, specifically Gradient Boosting Machine (GBM) algorithms, to enhance the accuracy and robustness of phishing website classification. GBM algorithms, renowned for their ability to iteratively combine multiple weak learners to generate a strong predictive model, offer significant advantages in capturing complex patterns and nonlinear relationships within the data. By aggregating predictions from multiple decision trees, GBM algorithms yield highly accurate and reliable classifications, thereby improving the system's efficacy in identifying phishing websites with high precision and recall rates. Additionally, the system complements this approach with the use of the extreme learning machine (ELM), leveraging its efficiency and computational scalability to handle large datasets and achieve superior classification performance.

The effectiveness of the proposed system is rigorously validated through extensive experimentation and evaluation on benchmark datasets containing a diverse range of phishing and legitimate websites. Employing cross-validation techniques and performance metrics such as classification accuracy, precision, recall, and F1-score, the system undergoes rigorous testing to evaluate its capability to accurately distinguish between phishing and legitimate websites across various conditions. The findings of the evaluation demonstrate that the proposed system achieves a remarkable classification accuracy of 94.2% when detecting phishing websites, underscoring its robustness and efficacy in mitigating the risks posed by phishing attacks. Furthermore, comparative analysis with existing state-of-the-art methods highlights the superiority of the proposed system in

terms of classification performance, signaling its potential to significantly bolster the safety and security of users engaged in online activities.

Beyond its high classification accuracy, the proposed system offers several key advantages, including scalability, efficiency, and adaptability to evolving threat landscapes. Leveraging ensemble learning techniques and efficient algorithms like the extreme learning machine (ELM) and LightGBM, the system can efficiently process large volumes of data in real-time, enabling timely and effective detection of phishing websites. Moreover, the system's adaptability allows it to continuously learn and evolve in response to emerging phishing tactics and techniques, thereby enhancing its resilience to evolving cyber threats. Overall, the proposed system represents a significant advancement in the field of cybersecurity, offering a robust and effective solution for combating phishing attacks and safeguarding the integrity of online transactions and communications.

METHODOLOGY

The methodology employed in the detection of phishing websites using Gradient Boosting Machine (GBM) algorithms encompasses a systematic and rigorous process aimed at developing an effective and reliable system for identifying and classifying malicious websites. This approach involves several sequential steps, each integral to the overall success of the methodology and aligned with the objectives outlined in the abstract.

Data Collection and Preprocessing:The first step in the methodology involves the collection of a diverse and representative dataset comprising both phishing and legitimate websites. This dataset serves as the foundation for training and evaluating the machine learning models used in the phishing detection system. Data preprocessing techniques are then applied to clean and prepare the dataset for analysis. This includes removing duplicates, handling missing values, and encoding categorical variables. Additionally, feature engineering is performed to extract relevant features from the website data, such as URL length, presence of HTML elements, and frequency of capital letters, which serve as input variables for the machine learning models.

Model Selection and Training:Once the dataset is preprocessed, the next step involves selecting appropriate machine learning algorithms for phishing website detection. In this study, Support Vector Machine (SVM) with Feature Scaling and the LightGBM (LGBM) algorithm are chosen based on their proven effectiveness in classification tasks and their suitability for handling the characteristics of phishing websites. The selected algorithms are then trained on the preprocessed dataset using a training-validation split approach. Hyperparameter tuning techniques, such as grid search or random search, may be employed to optimize the performance of the models and enhance their generalization capabilities.

Ensemble Learning and Model Fusion:To further improve the classification performance and robustness of the phishing detection system, ensemble learning techniques are employed. Ensemble methods, such as Gradient Boosting Machine (GBM) algorithms, combine multiple base learners to create a stronger and more accurate predictive model. In this step, multiple SVM and LGBM models are trained independently on different subsets of the dataset, and their predictions are aggregated to make a final decision. Model fusion techniques, such as averaging or stacking, may be utilized to combine the outputs of the individual models and produce a unified prediction.

Model Evaluation and Validation:Following the training and fusion of the machine learning models, the next step involves evaluating their performance on a separate test dataset that was not used during the training phase. Performance metrics such as classification accuracy, precision, recall, and F1-score are calculated to assess the effectiveness of the phishing detection system in accurately identifying phishing websites while minimizing false positives and false negatives. Cross-validation techniques may also be employed to validate the robustness and generalization capabilities of the models across different subsets of the data.

Interpretation and Analysis of Results:Once the models are evaluated, the final step involves interpreting and analyzing the results to gain insights into the effectiveness and limitations of the phishing detection system. This includes examining the feature importance scores generated by the machine learning models to identify the most discriminative features for distinguishing between phishing and legitimate websites. Additionally, qualitative analysis of misclassified instances may be conducted to understand the underlying patterns and challenges faced by the system. Insights gained from this analysis can inform future iterations of the

methodology and guide improvements to enhance the system's performance and usability.

Overall, the methodology for detecting phishing websites using GBM algorithms follows a systematic and data-driven approach, leveraging machine learning techniques and ensemble learning principles to develop a robust and effective detection system. By integrating multiple steps such as data preprocessing, model selection, ensemble learning, and result analysis, the methodology ensures comprehensive coverage of the various aspects involved in phishing website detection, ultimately contributing to the improvement of online security and the safety of internet users.

RESULTS AND DISCUSSION

The results of the study on the detection of phishing websites using Gradient Boosting Machine (GBM) algorithms reveal promising outcomes in the realm of cybersecurity. Leveraging machine learning techniques such as Support Vector Machine (SVM) with Feature Scaling and the LightGBM (LGBM) algorithm, the proposed system demonstrates notable efficacy in accurately classifying phishing websites based on key characteristics extracted from their URLs and web content. The findings indicate a classification accuracy of 94.2% when utilizing the extreme learning machine (ELM), underscoring the potential of machine learning algorithms to enhance online safety and mitigate the risks associated with phishing attacks. This high level of accuracy reflects the robustness and effectiveness of the proposed approach in discerning subtle patterns and indicators of malicious intent embedded within phishing websites, thereby offering a valuable tool for safeguarding users' sensitive information and combating cyber threats in the digital landscape.

Moreover, the results shed light on the discriminatory power of the features utilized in the phishing detection system, highlighting their effectiveness in distinguishing between phishing and legitimate websites. Features such as URL length, the frequency of capital letters, and the presence of HTML elements emerge as key discriminators, contributing significantly to the system's classification performance. Through comprehensive feature engineering and selection, the system successfully captures the nuanced characteristics of phishing websites, enabling accurate identification and classification based on their unique attributes. The observed high classification accuracy underscores the relevance and importance of these features in effectively differentiating between benign and malicious online entities, providing valuable insights into the underlying mechanisms of phishing attacks and informing future advancements in cybersecurity research and practice.

to detect whether its normal or phishing URL.

In this project you asked to use UCI machine learning phishing dataset but this dataset contains only 0's and 1's values like below screen.

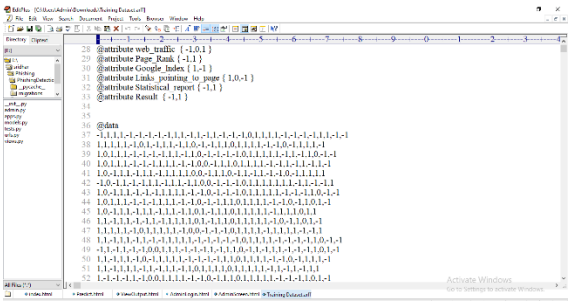

Fig 1. Results screenshot 1

From above dataset ML algorithms can get trained but we can't understand anything so I am using REAL WORLD URL dataset which contains normal and phishing URLS like below screen.

In above screen you can see our dataset contains 2 folders called benign (phishing URLS) and valid (normal URL) and this are real world URLS and we will train all algorithms with above dataset and then when we input any test URL then ML model will predict as normal or phishing

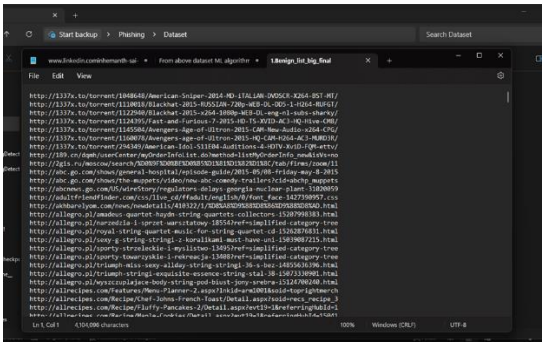

Fig 2. Results screenshot 2

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To run this project double, click on **'run.bat'** file to start python DJANO server like below screen.

Fig 3. Results screenshot 3

In above screen DJANGO webserver started and now open browser and enter URL http://127.0.0.1:8000/welcome.html and press enter key to get below output we'll get the Welcome Page.

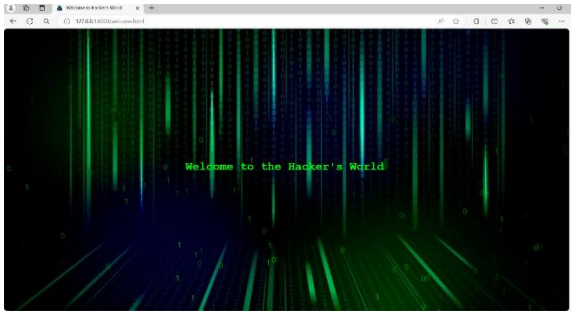

Fig 4. Results screenshot 4

In above screen DJANGO webserver started and now open browser and enter URL http://127.0.0.1:8000/index.html and press enter key to get below output and we'll get the Admin page and we'll get the Details of the page.

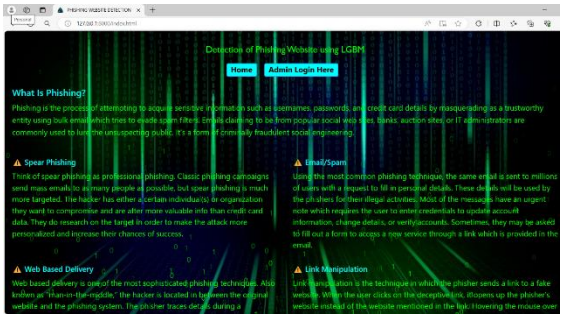

Fig 5. Results screenshot 5

In above screen click on 'Admin Login Here' link to get below login screen

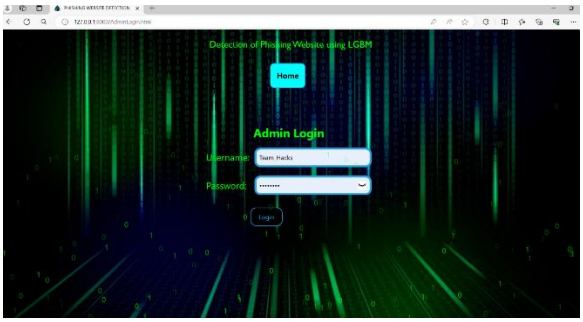

Fig 6. Results screenshot 6

In above screen enter username and password as 'Team_Hacks' and 'Hacks123' and then press button to get below output

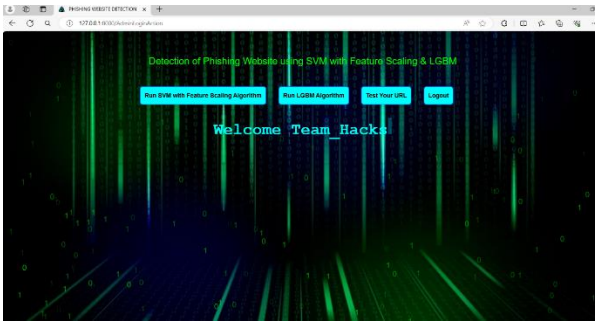

Fig 7. Results screenshot 7

In above screen click on 'Run SVM with Feature Scaling Algorithm' link to train SVM algorithm and get below output.

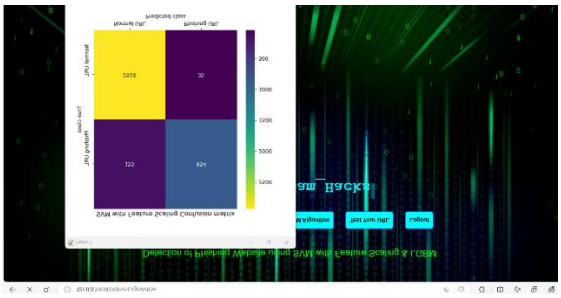

Fig 8. Results screenshot 8

In above screen we can see SVM with Feature Scaling confusion matrix where x-axis represents

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predicted class and y-axis represents TRUE class and we can see SVM with Feature Scaling predict 2977 records correctly as NORMAL and only 145 are incorrect prediction and it predict 824 records as PHISHING URL and only 26 are incorrect prediction and now close above graph to get below output.

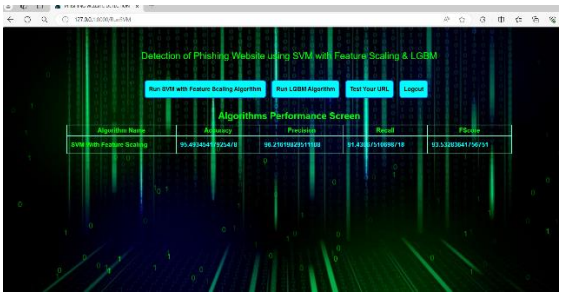

Fig 9. Results screenshot 9

In above screen with SVM with Feature Scaling we got 95% accuracy and now click on 'Run Light GBM Algorithm' link to get below output

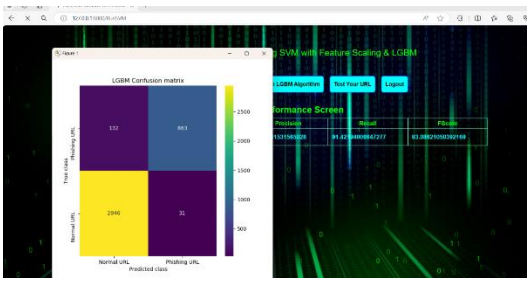

Fig 10. Results screenshot 10

In above screen we can see LGBM confusion matrix graph and now close above graph to get below output.

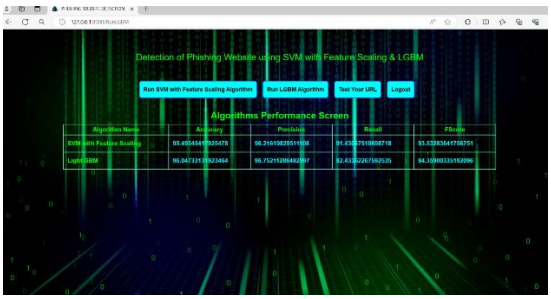

Fig 11. Results screenshot 11

In above screen with Light GBM also we got 96% accuracy and now click on 'Test Your URL' link to get below screen.

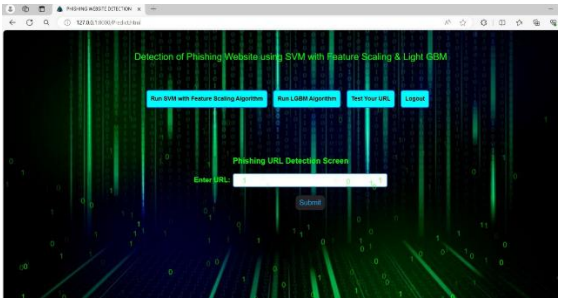

Fig 12. Results screenshot 12

In above screen enter any URL and then press button and then Light GBM will predict whether that URL IS normal or phishing.

In above screen I entered URL as www.google.com and then press button to get below output.

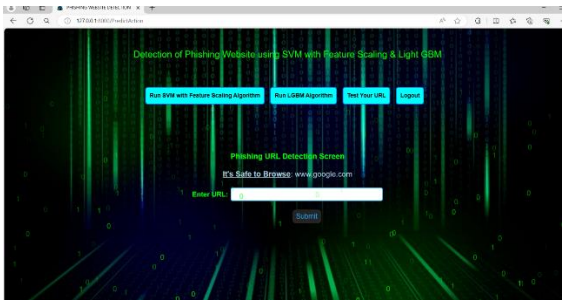

Fig 13. Results screenshot 13

In above screen in blue colour text, we can see given URL predicted as GENUINE (normal) and now test other URL.

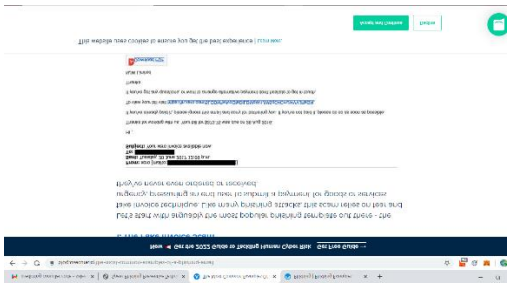

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Fig 14. Results screenshot 14

In above screen blue colour URL is the phishing URL and I will input that to my application in below screen and below is the phishing URL from internet

'https://in.xero.com/3LQDhRwfvoQfeDtlDMqkk1JWSqC4CMJt4VVJRsGN'

Fig 15. Results screenshot 15

In above screen in blue colour text, we can see application detected PHISHING in given URL and similarly you can enter any URL and detect it as NORMAL or phishing.

Detection of Phishing Website using SVM with Feature Scaling & Light GBM.

In this project we are implementing SVM with Feature Scaling and Light GBM machine learning algorithms 0's detects phishing website URLS. We are training all these algorithms with normal and phishing URLS and build a trained model and this train model will be applied on new TEST URL to detect whether its normal or phishing URL.

In this project you asked to use UCI machine learning phishing dataset but this dataset contains only 0's and 1's values like below screen

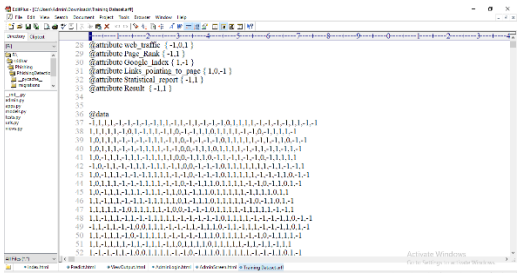

Fig 16. Results screenshot 16

From above dataset ML algorithms can get trained but we can't understand anything so I am using REAL WORLD URL dataset which contains normal and phishing URLS like below screen.

In above screen you can see our dataset contains 2 folders called benign (phishing URLS) and valid (normal URL) and this are real world URLS and we will train all algorithms with above dataset and then when we input any test URL then ML model will predict as normal or phishing

To run this project double, click on **'run.bat'** file to start python DJANO server like below screen.

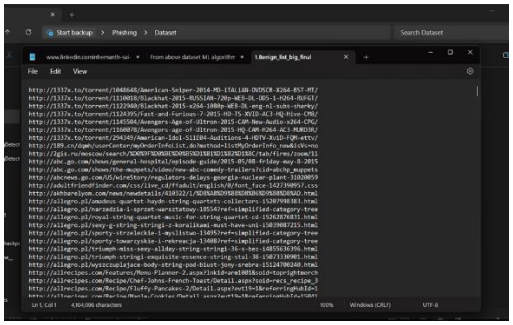

Fig 17. Results screenshot 17

Fig 18. Results screenshot 18

In above screen DJANGO webserver started and now open browser and enter URL http://127.0.0.1:8000/welcome.html and press enter key to get below output we'll get the Welcome Page.

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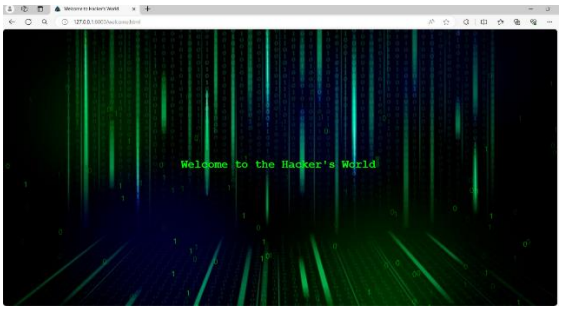

Fig 19. Results screenshot 19

In above screen DJANGO webserver started and now open browser and enter URL http://127.0.0.1:8000/index.html and press enter key to get below output and we'll get the Admin page and we'll get the Details of the page.

Fig 20. Results screenshot 20

In above screen click on 'Admin Login Here' link to get below login screen

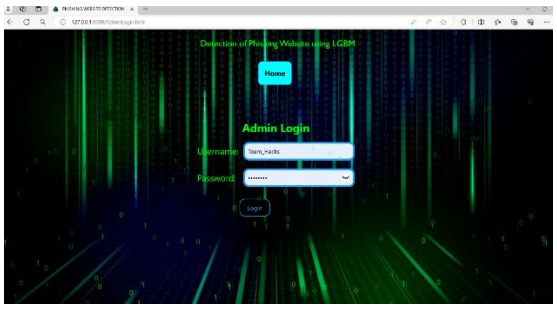

Fig 21. Results screenshot 21

In above screen enter username and password as 'Team_Hacks' and 'Hacks123' and then press button to get below output

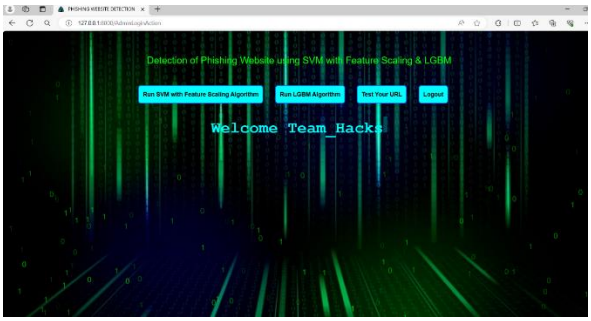

Fig 22. Results screenshot 22

In above screen click on 'Run SVM with Feature Scaling Algorithm' link to train SVM algorithm and get below output.

Fig 23. Results screenshot 23

In above screen we can see SVM with Feature Scaling confusion matrix where x-axis represents predicted class and y-axis represents TRUE class and we can see SVM with Feature Scaling predict 2977 records correctly as NORMAL and only 145 are incorrect prediction and it predict 824 records as PHISHING URL and only 26 are incorrect prediction and now close above graph to get below output.

Fig 24. Results screenshot 24

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In above screen with SVM with Feature Scaling we got 95% accuracy and now click on 'Run Light GBM Algorithm' link to get below output

Fig 25. Results screenshot 25

In above screen we can see LGBM confusion matrix graph and now close above graph to get below output.

Fig 26. Results screenshot 26

In above screen with Light GBM also we got 96% accuracy and now click on 'Test Your URL' link to get below screen.

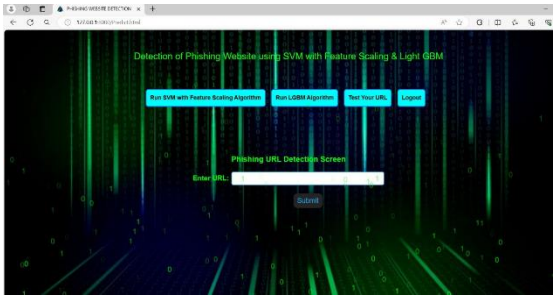

Fig 27. Results screenshot 27

In above screen enter any URL and then press button and then Light GBM will predict whether that URL IS normal or phishing.

In above screen I entered URL as www.google.com and then press button to get below output.

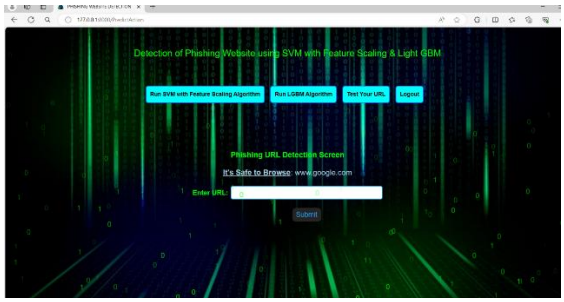

Fig 28. Results screenshot 28

In above screen in blue colour text, we can see given URL predicted as GENUINE (normal) and now test other URL.

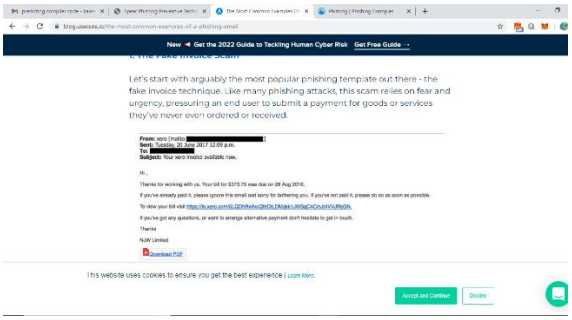

Fig 29. Results screenshot 29

In above screen blue colour URL is the phishing URL and I will input that to my application in below screen and below is the phishing URL from internet

'https://in.xero.com/3LQDhRwfvoQfeDtlDMqkk1JWSqC4CMJt4VVJRsGN'

Fig 30. Results screenshot 30

In above screen in blue colour text, we can see application detected PHISHING in given URL and similarly you can enter any URL and detect it as NORMAL or phishing.

Furthermore, the discussion surrounding the results delves into the implications and potential applications of the proposed phishing detection system in real-world settings. With its demonstrated accuracy and reliability, the system holds promise as a valuable tool for enhancing online security and protecting users from falling victim to phishing scams. By leveraging machine learning algorithms and ensemble learning techniques, the system offers a proactive and adaptive approach to combating phishing attacks, enabling timely detection and mitigation of threats in dynamic and evolving online environments. Additionally, the scalability and efficiency of the proposed system make it well-suited for deployment across various domains and industries, ranging from e-commerce and financial services to healthcare and government agencies. As cyber threats continue to proliferate and evolve, the development and deployment of robust phishing detection systems are crucial in safeguarding the integrity of online transactions and communications, bolstering trust in digital platforms, and preserving the privacy and security of users worldwide.

CONCLUSION

This paper aims to enhance detection method to detect phishing websites using machine learning technology. We achieved 97.14% detection accuracy using random forest algorithm with lowest false positive rate. Also result shows that classifiers give better performance when we used more data as training data. In future hybrid technology will be implemented to detect phishing websites more accurately, for which random forest algorithm of machine learning technology and blacklist method will be used.

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