Fishing for Phish: an Exploration of Web-Based Features for the Purposes of Phishing Detection

AP Capstone Research

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ABSTRACT

With the rise of the Information Technologies industry, the value of personal information and data has skyrocketed. This has fueled cybercrime, up 600% due to the exploitations of situations such as the Covid-19 Pandemic and the Russian invasion of Ukraine (PurpleSec LLC, 2021). Phishing in particular has been a common cause of security breaches, data theft, and malware distribution (PurpleSec LLC, 2021). This research aimed to analyze web-based phishing via comparison to legitimate domains using classification and regression machine learning techniques and set forth a simple framework for doing so. By following a mixed methodology incorporating page source and visual stimuli related features, the researcher hypothesized that data trends based on intent could be found, and incorporated over time into future machine learning methods. However, not enough data regarding phishing websites was collected to come to any substantial conclusions regarding this hypothesis, but the creation of a python module to automate scraping and feature extraction, feature selection, and other machine learning processes was programmed, allowing for adaptive feature analysis in the future, and a website was developed, to showcase the module in a more simplistic fashion and collect data in order to aid future phishing detection.

INTRODUCTION

In *Psychology: The Influence of Persuasion*, Robert B. Cialdini Ph.D. characterized the 6 principles of persuasion as “Weapons of Influence”. This terminology insinuates the danger of persuasion techniques and tactics and accurately represents the current state of the information security sector. The “human firewall”, as expressed by Nathaniel Joseph Evans in *Information technology social engineering: an academic definition and study of social engineering - analyzing the human firewall*, is easily exploited using social engineering in combination with persuasive techniques and deception. Phishing (misleading individuals to reveal sensitive information) in particular is the cause of 90% of information technology breaches (Sibrian, 2020). Consequently, this research intends to uncover common patterns and trends via data analysis of the page source and appearance of phishing websites. The researcher intends to use machine learning (explained by Priyadharshini Devarajan as the technique of using computer algorithms to find information intuitively and learn from data without being explicitly programmed to do so) techniques (Sodhi et al., 2019, as cited in Priyadharshini, 2017) to analyze the variations between phishing websites and legitimate websites to better understand the relation of certain features to the classification of a website from a psychological perspective to support predictive phishing classification and detection efforts.

Many of the current solutions regarding phishing are not preventative, but reductive. For example, blacklisting, where identified phishing sites are blocked, may help mitigate damages caused by these sites but does nothing regarding new sites or phishing on a more global scale (Chiew et al., 2019). However, machine learning (the process of using artificial intelligence to analyze data, and then classifying and/or making predictions regarding that data) is reactive, using analyzed patterns and trends from input data to make generalized predictions regarding, and classify, new data in a process known as regression (Sodhi et al., 2019). By taking a machine learning approach to phishing detection and analysis, features (indicators of a phishing website) can be more effectively and accurately analyzed, patterns and trends in the phishing dataset can be deduced, and predictions based on these patterns can be made. These results can lead to greater insight into phishing, which can then contribute to phishing detection efforts, and allow for further psychological analysis, specifically regarding the persuasive reasoning behind and the effectiveness of certain features relative to the “human firewall”.

While it is difficult to predict the outcome of a machine learning model due to the excessive amount of variable data (in the context of a human analysis at least), it is reasonable to predict that the patterns and trends of phishing websites will reveal commonalities in phishing and to assume that these commonalities have psychological motivation and intent behind them, because of the deceptive nature of phishing websites. With this in mind, the hypothesis can be made that phishing websites will have similar data trends and patterns in order to mislead users and that the main feature differences between the real and legitimate sites are correspondent with intention, and, because of this, these differences can be analyzed for psychological impact and effectivity.

LITERATURE REVIEW

Information technology is a constantly evolving field and phishing is a constantly evolving practice. With the rise of new communications technology, new social engineering strategies have arisen to help aid cyberattackers. It is important to analyze prior research regarding human susceptibility and vulnerability to psychological manipulation, as well as research regarding phishing machine learning analyses before conducting research relative to gaps in prior literature.

In the dissertation *Information technology social engineering: an academic definition and study of social engineering - analyzing the human firewall* Nathaniel Joseph Evans sought to analyze social engineering in the information technology field. Evans defined social engineering as “the exploitation of human vulnerabilities in a cyber-context”, and analyzed various psychological persuasive models (for example the trust model**,** where the attacker abuses the benevolence and integrity of a person for personal gain) and principles (for instance how linguistics can be used to manipulate people) in order to gain a better understanding about the human decision-making process, and how it could be influenced.

Furthermore, Robert B. Cialdini compiled overall findings over years of study and research into an educational text on the psychology behind persuasion. Cialdini mainly focuses on the principles of psychological persuasion (or, as he calls them, “weapons of influence”) which could be used for the purpose of social engineering. These principles include the contrast principle, reciprocation, consistency and commitment, social proof, the friendship principle, authority, and the scarcity principle. Each of these principles influences the decision-making process, largely because as society has changed, humans have evolved and sub-consciously automated aspects of the decision-making, which these principles exploit. Cialdini dives into each of these principles, providing examples of how they work, how they are effectively used, and countermeasures against each one.

Moreover, Rosana Montañez, Edward Golob, and Shouhuai Xu explored types of human cognitive exploitation in the context of social engineering in information technology. The authors determined four major components of cognition: perception, working memory, decision making, and action, which became the focus of the study. Some short-term impacts on cognition the authors researched and analyzed are workload (the demand of a cognitive task), stress (the importance of a cognitive task; causes tunneling/ignorance), and vigilance (change in cognitive performance over time when working on a task). The authors acknowledged some long-term factors that influenced behavior and therefore possible responses to a social engineering attack, including personality, expertise, social differences, and culture. Overall, the authors concluded that the decision-making could be manipulated into immediate action by abusing automatic behavioral instincts developed from long-term psychological factors.

Additionally, Jeyakumar Samantha Tharani and Nalin A. G. Arachchilage explored the strategies used by phishers to mimic and create phishing URLs in order to trick internet users in *Understanding phishers' strategies of mimicking uniform resource locators to leverage phishing attacks: A machine learning approach*. The authors first reviewed prior research regarding feature selection (a variety of methods for choosing which features to analyze and use in the machine learning process) and found a lack of analysis of specific features of phishing URLs, so the authors used the information gain (calculates the amount of information of a feature relative to the probability that it appears) and chi-squared (tests the independence of two features) feature selection methods on the dataset provided by Dr. Colin Choon Lin Tan. The authors determined that *PctNullSelfRedirectHyperlinks*, *FrequentDomainNameMismatch*, *SubmitInfoToEmail*, *PctExtResourceUrls*, *InsecureForms*, *ExtMetaScriptLinkRT*, *PctExtNullSelfRedirectHyperlinksRT*, *NumDash*, *IframeOrFrame*, *NumSensitiveWords*, *PctExtHyperlinks*, *NumNumericChars* and *NumDots* were the most significant features, with null self-redirect hyperlinks present in a URL and a different domain name in the majority internal site hyperlinks being the most commonly utilized techniques out of those analyzed.

Lastly, Ankit Kumar Jain and B. B. Gupta researched phishing using visual similarity in *Phishing Detection: Analysis of Visual Similarity Based Approaches.* Specifically, Jain and Gupta analyzed deceptive website appearances, including techniques such as embedding images to hide content and similar appearances and Favicon image icons. Methods such as pixel-based analysis and image extraction were performed in order to collect data regarding style and layout relative to the page source that can be compared to the original page for visual similarity analysis. Jain and Gupta discussed the relationship between image-processing and visual similarity approaches, with time and computational consumption, as well as a lack of data regarding zero-hour (immediate) phishing detection.

Overall, existing research on approaches to analyzing web-based phishing techniques and features in the information technology field and psychological research on persuasion and the decision-making process helped guide this study. Due to the recency of the field of phishing in information technology, there are gaps in research, particularly regarding the psychological understanding and analysis of phishing features, especially in the context of a phishing and legitimate comparison of page and image features.

METHODOLOGY

In regards to a procedure, it is difficult to be specific, as machine learning is an adaptive methodology, where one decision induces another, and experimentation is encouraged to obtain unique data that may be useful for accurate phishing detection. However, a formulated plan was created prior to conducting the methodology, involving many resources that can be used for future phishing detection, all of which can be found in the footnote below, and have a separate appendix entry. In order to find persuasive methods and patterns employed in web-based phishing scenarios, the researcher initially chose a machine-learning content-analysis based methodology to gain a better understanding of web-based phishing, based on prior proposed trends, patterns, and research and expanding upon the method found in *Understanding phishers' strategies of mimicking uniform resource locators to leverage phishing attacks: A machine learning approach* by combining it with a new set of image-based features determined based on prior research, in particular *Phishing Detection: Analysis of Visual Similarity Based Approaches*, as well as image-hashing techniques provided by the imagehash python module (in particular the perceptual and difference hash algorithms due to their comparison-based natures) to use visual similarity for immediate detection based on respective prior hash values. By providing an alternative image-hashing technique, it allows the module to be repurposed and utilized for hash-based detection purposes, as well as serves to optimize runtime. The researcher determined that a machine learning approach on the datasets *Phishing Dataset for Machine Learning: Feature Evaluation* (originally found at [1],

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[1] https://doi.org/10.17632/h3cgnj8hft.1
[2] https://phishstats.info/
[3] https://domcop.com/top-10-million-domains
[4] https://github.com/xanmankey/FishingForPhish.git
[5] https://github.com/xanmankey/PhishAI.git
[6] https://phish-ai.vercel.app/
[7] https://pypi.org/project/FishingForPhish/0.3.0/
[8] https://fishingforphish.readthedocs.io/en/latest/

consists of 10000 instances and 48 attributes, 5000 legitimate and 5000 phishing), *phish_score.csv* (originally found at [2], the top 500 phishing websites were selected via the provided phish_score ranking system), and *top_ten_million.csv* (originally found at [3], the top 500 legitimate websites were selected via the Open Page Rank ranking system), with 6 resulting datasets (full and ranked feature versions of page-based only, image-based only, and combined feature datasets) would be an effective mix of page and image-based data for the context of this research, allowing for comparisons and analysis while also taking into account the time and computational costs of the methodology. In terms of software, the programs Weka and Python Weka Wrapper3 were chosen, in particular, due to the useful visualizations of the machine learning process, and VS Code due to prior experience with the Integrated Developer Environment (IDE). In regards to machine learning algorithms, the researcher chose to experiment with the Correlational, Information Gain, and Chi-squared filter feature selection algorithms (in accordance with the research *Understanding phishers' strategies of mimicking uniform resource locators to leverage phishing attacks: A machine learning approach*; specifically expanding upon the ranked feature subsets provided by these algorithms in order to obtain a set of features) and the classification algorithms Jrip, J48, and Naive Bayes, primarily because of their ease of interpretation and analysis and effectiveness regarding classification and regression. Finally, the researcher decided to include a human analysis of the resulting data in order to apply background psychological knowledge to the data analysis process to draw non-numerical conclusions and provide meaning to the outputted data. The researcher also decided to create a collection of the data at [4] to reflect the dynamism of data collection, as well as a website integrated with the Github repository at [5] (found at [6] when hosted, currently offline, as the website is reliant on the python module, and thus a stable release should be waited for before attempting further user-driven data collection) showcasing the model and allowing for further data collection, to allow for easier collaboration, replication, and future research.

A machine learning method is especially effective, as phishing attempts are constantly changing, so an approach that can analyze large amounts of different quantitative and qualitative data and determine informational features and numerical patterns is essential. However, as the researcher manually performed the dataset creation steps, the process became exhaustive, with 6 different sets of features as well as 18 different machine learning model results, and ultimately led to the python module FishingForPhish, an automation of these processes with additional support for expansions of this methodology, and the website built off of the module, PhishAI, for easy testing and access to data via a simple web API. FishingForPhish uses the Selenium Webdriver software (in the case of this research, Firefox was used for security purposes, in addition to a 20.04 Ubuntu Virtual Machine to isolate the host device to protect against automatic Javascript malware infection, as well as Proton VPN (a VPN service) and Open VPN (a VPN protocol), to protect any data that might be revealed otherwise) to scrape web data from a list of provided URLs, which can then be used for analysis. PhishAI uses MongoDB (a cloud database hosting provider) in addition to the FishingForPhish module to create a system where data can constantly be updated and accessed and the module can easily be experimented with. The replicability of Python modules and the consistency of data storage also helps drive further research. The python module (at [7]) and the documentation (at [8]) serve to help future researchers examine new features regarding phishing and provide an easily replicable web-scraping alternative. The usage of the module followed by the researcher in accordance with the experimental design can be found in figure 1 below.

Figure 1: Example usage of the FishingForPhish module

```
def main():
   # Initialization
   run = startFishing()
   run.initializeAll()

   fisher = scrape(urlFile="data/urls.txt",
     dataDir="data",
     driver=run.driver,
     classVal=0)

   # Initialization of the page analyzer
   pageData = page()
   fisher.addAnalyzer(pageData)

   # Initialization of the image analyzer
   imageData = image()
   fisher.addAnalyzer(imageData)

   # Once the analyzers have been added, it doesn't matter what
   # instance the goFish method is called with
   fisher.goFish()
   print(pageData.features)
   print(imageData.features)

   # Data Combination
   # The features generated from the other instances are then used
   # when dealing with (creating datasets, classifying, ect.) data
   # Takes the same arguments as the scrape class
   DC = saveFish(urlFile="data/urls.txt",
     dataDir="data",
     driver=run.driver,
     classVal=0,
     analyzers=fisher.analyzers,
     allFeatures=fisher.allFeatures,
     allFeatureNames=fisher.allFeatureNames)
   DC.createDatasets()
   DC.classify()
   print(DC.score)
   print(DC.classifications)

   DC.closePWW3()
   DC.closeSelenium()

if __name__ == "__main__":
   main()
```

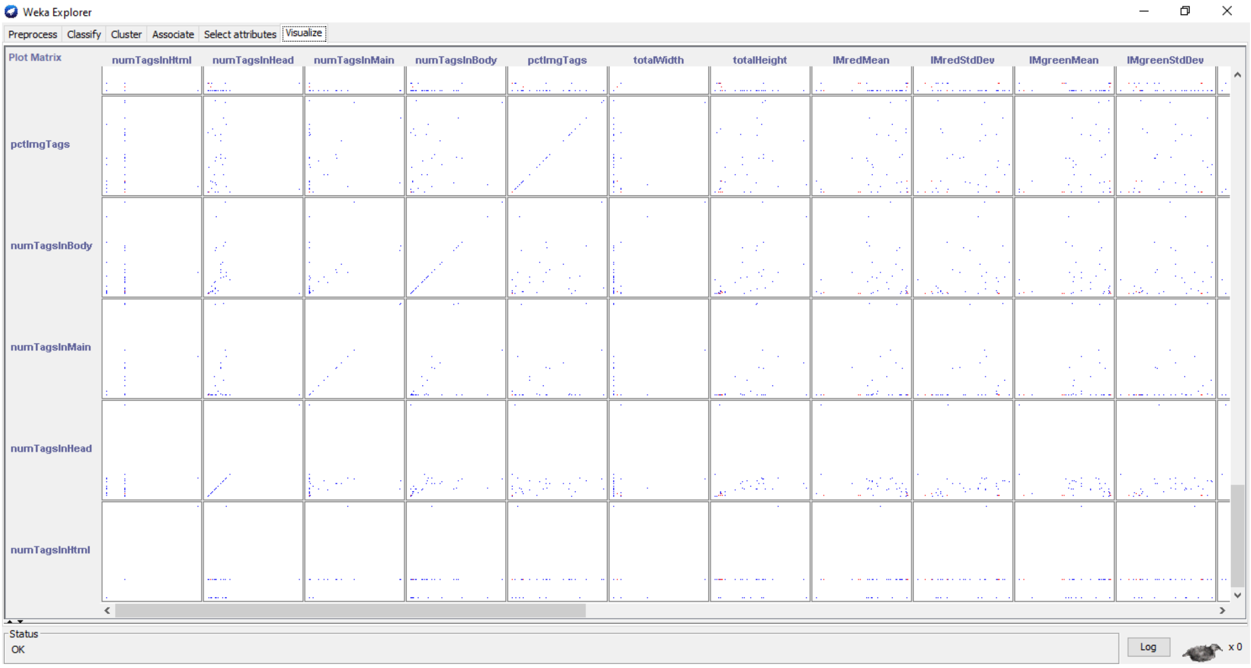
In order to understand the execution of the methodology, it is imperative to understand the structure of the module that it inspired. The FishingForPhish module is broken down into a few key classes: the startFish class for setup and initialization, the scrape class, to automate the web-scraping process, the analyzer class, a base class with guidelines to allow for analyzer creation that is implemented during the scraping process, the pageAnalyzer and imageAnalyzer classes, inheriting from the analyzer base class and used to analyze the parsed URL data to return respective feature data, and the saveFish class, for working with machine learning and datasets.

While machine learning may be an effective method for a content analysis of phishing, this methodology is not without its limitations. Visual and numerical datasets were included to get a comprehensive content analysis, but overall only 300 websites were initially considered. In the global scope of phishing, especially in the context of an evolutionary field, this amount is not substantial enough to justify any great conclusions. Additionally, the evolutionary nature of phishing and a popular aversion to web scraping (extracting web-based data for numerical and other applications) makes it hard to parse and analyze phishing and legitimate websites alike. However, the data collected and analyzed from this methodology and from the website, as well as the provided module, can help support other research and provide a good foundation for further experimentation.

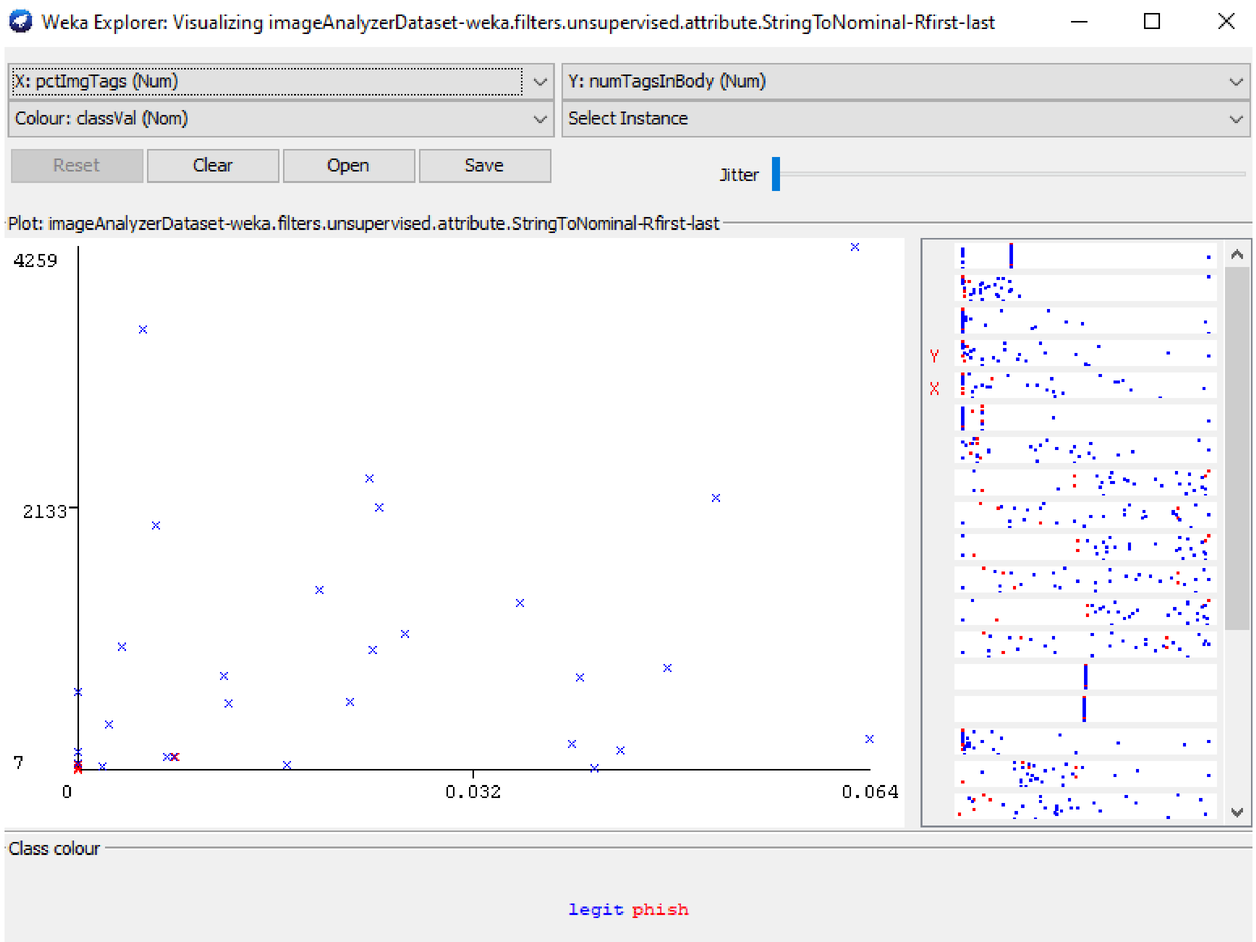
RESULTS

Quantitative data was obtained for two sets of features built on two analyzers: the pageAnalyzer (a version of Dr. Tan's original scraping code, with added python3 functionality and adapted to act as an analyzer class) and the imageAnalyzer (based on the features selected from the research at *Phishing Detection: Analysis of Visual Similarity Based Approaches*). The data can be found in two places: either by downloading the data.db file that contains the data from this research and working with it via an SQL database engine or by accessing the API set forth at [6] and downloading the data from individual MongoDB collections or downloading the entire MongoDB cluster (which is updated over time with the website). Out of the 300 selected websites, data for 37 was scraped, with a near 6:1 legitimate to phishing ratio. The datasets and scraped data can be found in .arff dataset files in the *datasets* directory at [4] and in the *css*, *html*, and *screenshots* directory respectively. In order to gain a full understanding of the data, it is recommended to load the datasets in Weka GUI, so as to take advantage of the automated graphing capabilities found under the *Visualize* tab, which can be used to better grasp the meaning of data through visualization in order to determine relationships. Examples of this process can be found in figures 2.1 and 2.2 below, specifically a matrix of feature versus feature graphs regarding the imageAnalyzer dataset, and specific adaptations and customizations of a single graph.

Figure 2.1: Matrix of feature versus feature graphs



<u>Figure 2.2: Customizing a single Weka graph using customization capabilities</u>



The full sets of features can be found and are elaborated upon, with the page features in more depth at *Understanding phishers' strategies of mimicking uniform resource locators to leverage phishing attacks: A machine learning approach* and the image features in figure 3 below.

Figure 3: Documented set of image features

1. numTagsInHtml: Number of tags DIRECTLY (does not include nested tags) inside the HTML tag
2. numTagsInHead: Number of tags directly inside the Head tag
3. numTagsInMain: Number of tags directly inside the Main tag
4. numTagsInBody: Number of tags directly inside the Body tag
5. pctImgTags: Percentage of all tags that are image tags
6. totalWidth: Total width of the website (in px)
7. totalHeight: Total height of the website (in px)
8. IMredMean: The mean red value of the full website screenshot
9. IMredStdDev: The mean red standard deviation of the full website screenshot
10. IMgreenMean: The mean green value of the full website screenshot
11. IMgreenStdDev: The mean green standard deviation of the full website screenshot
12. IMblueMean: The mean blue value of the full website screenshot
13. IMblueStdDev: The mean blue value of the full website screenshot
14. IMalphaChannel: A binary; checking if imagemagick identified an alpha channel or not from the full website screenshot.
15. IMgamma: The gamma value of the full website screenshot.
16. numBoldTags: The number of tags that have a font-weight property greater than the normal, 400.
17. averageFontWeight: The total font-weight divided by the number of tags with a font-weight (so all with text).
18. mostUsedFont: The most common font used throughout all tags with the font-family property.
19. averageFontSize: The total font size (in px) divided by the number of tags with the font-size property.
20. numStyles: The number of tags with a font-style or text-decoration value that isn't equal to normal or none.
21. mostUsedStyle: The most common style through all tags with a font-style or text-decoration value that isn't equal to normal or none.
22. pctItalics: The percentage of style tags that have the italic property set.
23. pctUnderline: The percentage of style tags that have the underline property set.

Additionally, the top ten ranked features for the page and image features, as well as the combined ranked features for the ranked dataset (composed of the top 10 selected ranked features overall following the combination of the two feature datasets), are listed in figures 4.1, 5.1, and 6.1 below, with the figure index corresponding with the set of features and related information.

Figure 4.1: Ranked page feature data

Ranking	**Feature**
1	**ExtMetaScriptLinkRT**
2	**PctExtNullSelfRedirectHyperlinksRT**
3	**NumNumericChars**
4	**PathLength**
5	**PathLevel**
6	**NumAmpersand**
7	**RandomString**
8	**NumQueryComponents**
9	**UrlLength**
10	**HostnameLength**

Figure 5.1: Ranked image feature data

1	**mostUsedFont**
2	**averageFontSize**
3	**numBoldTags**
4	**favicon**
5	**numTagsInMain**
6	**pctImgTags**
7	**IMgreenMean**
8	**IMredMean**
9	**pctUnderline**
10	**IMblueStdDev**

Figure 6.1: Combined ranked feature data

1	**averageFontSize**
2	**mostUsedFont**
3	**numBoldTags**
4	**NumDots**
5	**PathLevel**
6	**mostUsedStyle**
7	**favicon**
8	**UrlLength**
9	**pctUnderline**
10	**totalHeight**

Furthermore, classification data for the page, image, and ranked data can be found in the appendix in 3 sets of figures: 4.2, 4.3, 4.4, 5.2, 5.3, 5.4, and 6.2, 6.3, 6.4 respectively. For the full output files, view the *output* directory at [4]. An example classification output file can be seen in figure 6.3 below.

Figure 6.3: Jrip model output (all features)

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          32               86.4865 %
Incorrectly Classified Instances         5               13.5135 %
Kappa statistic                          0.4669
Mean absolute error                      0.1389
Root mean squared error                  0.3604
Relative absolute error                 48.4384 %
Root relative squared error             96.607  %
Total Number of Instances               37

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.935    0.500    0.906      0.935    0.921      0.470    0.895     0.968     legit
                 0.500    0.065    0.600      0.500    0.545      0.470    0.895     0.500     phish
Weighted Avg.    0.865    0.429    0.857      0.865    0.860      0.470    0.895     0.892

=== Confusion Matrix ===

  a  b   <-- classified as
 29  2 |  a = legit
  3  3 |  b = phish
```

There are a couple of key things to note regarding the Jrip model output seen in figure 6.3, specifically the accuracy percentage, 86.4865%, and the confusion matrix, which represents the number of correct and incorrect classifications for each class, defined more technically as true positives (for example, there are 3 true positives, 3 sites that were classified as phishing and are phishing websites) false positives, true negatives, and false negatives. Additionally, it's important to note that the classification models selected serve to generate interpretable data to allow for a better understanding of how the model learned (for example the Jrip algorithm functions by generating subsets of feature rules), and in this case, although not reflected in the screenshot (the full output files can be found at [4] if desired), Jrip outputs the rules *(numTagsInHead <= 8) and (numTagsInHead >= 7) => classVal=phish (5.0/0.0)* and *=> classVal=legit (32.0/1.0)*, where => is prefaced by a rule (if one exists).

Finally, the database functionality (the error functionality in particular) provided by the FishingForPhish module allows for further analysis and adaptation of the code. Running SQL (a programming language used for managing and manipulating data) commands known as queries on the data.db database at [4] allows users access to a variety of data. This includes a complete set of errors and their associated URLs with the command *SELECT * FROM errors*, where 404 (page not available) and 403 (page available, but forbidden from user access) error codes were more prevalent than any other error condition, as seen in the error distribution, which can be calculated via SQL *COUNT* syntax and logic, the complete feature data sets, except accessible via a database format, the metadata of a scraped URL, which includes a list of all successfully-scraped URLs and the original time the scraping process begun, useful for obtaining runtime and experimental information regarding the module, and associated hash values (in particular perceptual and differential hash values) for each URL, where SQL *JOIN* functionality can be used on the *urls* column to automate hash comparisons.

DISCUSSION

This research was driven by a lack of psychological analysis and comparison of phishing and legitimate features, but inaccuracies during data collection resulted in skewed data and inhibited analysis. These inaccuracies are demonstrated in figure 6.3, where the classification (86.4865%) is deceptively high, and represents an unintentional failure, defined in *Failure Modes in Machine Learning* as “a formally correct but completely unsafe outcome” (amarshal et al., 2021). The confusion matrix found in the model output displays the uneven class distribution via the model output, which influenced the way in which the model learned how to classify phishing versus legitimate websites. More accurately, it’s not the class ratio of legitimate to phishing websites (6:1) itself that influences the way the model learns, but rather the lack of data regarding phishing websites that renders the ability to find trends and patterns insignificant for any detection outside of the original training data. This issue with the model is amplified by scraping errors that were unaccounted for upon running the module, which can be found in the errors table in the database at [4], with failing to account for websites that were blacklisted or taken down a primary cause of inaccurate data. The SMOTE Weka filter was not utilized in order to rebalance the classes, due to the proportion of phishing feature data that was error-related and yet still scraped. Additionally, if the rules provided by the Jrip model are examined, there is no rule correlated with a legitimate website classification, as seen in *=> classVal=legit (32.0/1.0)* at [4], which implies that Jrip was unable to find any patterns in the data, and classified as legitimate without any reasoning or trend, further exposing the inaccuracies of the trained model.

As a consequence of feature data inaccuracies caused during the scraping process, all the other data from this experiment, while structured and organized effectively for future research and analysis, would lead to inaccurate conclusions if utilized for psychological analysis or machine learning-based phishing detection. For example, if any of the models were to be utilized for phishing detection in a web-browsing context, they would likely experience low classification accuracies and undesirable outcomes, mostly due to inaccurate data being an unintentional failure of the trained model. Additionally, the lack of training and testing in other environments further limits the applicability of the models. However, the auto-generation of this structure does lend itself to further experimentation, and the error functionality provided by the module allows for further streamlining of the methodology and seamless implementation in future research. Due to the commonality of 404 and 403 error codes, as well as the prevalence of a temporary loss of internet (most likely due to the kill switch functionality of Proton VPN, as internet resumed shortly after a disconnection during the experiment), the siteValidation and checkInternet methods were added to the scrape class of the module, to check for these errors accordingly in order to reduce data inaccuracies regarded to blacklisted or suspended webpages, as well as suspend the program in the case of a disconnection to avoid any external influences on the experiment. The resume and exitHandler methods were also added to the scrape class to add convenience and structure, automating proper shutdown of the program upon an exception and allowing users to restart the program in case of a raised exception midway through. A few exceptions still remain independent, but this issue regarding error distribution can be solved over time by checking for a specific exception and updating the database with a consistent error accordingly.

Although the original research question was not directly answered, by providing an adaptable module that automates the web-scraping process and allows for user-defined feature analysis, the time spent during data collection, training, feature selection, and classification is minimized, allowing for more in-depth feature analysis and benefitting future research.

CONCLUSION

Limitations

One of the issues with classifying phishing versus legitimate websites is the volatility of websites. If a phishing website is listed as so on a major phishing database (OpenPhish, PhishTank, PhishStats, ect.), then the host of the website might shut down the website. This and its associated errors made the preprocessing of data difficult and occasionally inconsistent. Also, websites constantly change, and as links are added and visuals change, the raw data shifts as well. This hurts the replicability of the methodology, as the nature of the data being researched is constantly changing, as well as contributes to an uneven class distribution and outdated data. The nature of phishing, constantly evolving in order to deceive current users and adapt to current social and cultural climates, impacts the significance of the data, as the data will constantly be changing in the future, and requires immediate and adaptive countermeasures. However, it is important to get as much data about phishing websites as possible, primarily due to the importance of correctly classifying a phishing website as such, and the possible repercussions of a false negative, or classifying a phishing website as legitimate. Despite all the inaccuracies, the purpose of phishing remains constant, and with it, it is still hypothesized that there are common trends and patterns that are unlikely to change, allowing prediction via machine learning regression algorithms to maintain some degree of accuracy as long as detection efforts continue to adapt at a similar pace to phishing efforts, which the adaptability and replicability of FishingForPhish may be able to help prove.

Implications

The purpose of this research was to collect and analyze page-based and image-based data in order to find useful patterns regarding phishing websites versus legitimate websites that can potentially be used in classification and regression. While data was collected, its inaccuracies due to the volatility of websites hurt the trained models and limited the applicability and efficacy of phishing detection, preventing any strong conclusions regarding the effectiveness of combined page and image-based phishing detection and psychological analysis of the features set forth. However, an automated and adaptable method following is set forth in the programmed module, and can be useful to further researchers utilizing web scraping and machine learning processes, and could be expanded to a greater audience if the programmatic aspects were minimized, particularly if a GUI were to be implemented.

Further Research

Further research should be conducted to minimize the outliers and errors caused by the volatility of phishing and legitimate websites. The tools set forth by this research simplify the process the methodology was built upon via interactive visualization, and will contribute to data collection that can be used for future research. There's still a lot of work to be done, and a lot that needs to be addressed, for example, PhishAI (the website found at [6]), was created for the purpose of testing the current ranked model, as well as adding new data for future use, but will not be hosted until a successful experiment with accurate data is conducted using the module and possible security threats on the website and the module are addressed. When the website is hosted, it will aim to expand the audience by simplifying the process the methodology was built upon via interactive visualization, and will contribute to data collection that can be used for future research.

Similarly, the FishingForPhish module provides adaptive functionality that follows the methodology and aids future feature analysis by providing an implemented method for adaptive data collection regarding features, and allows for new implementations and improvements, with some possibilities being the addition of psychology-based python libraries (for example PsychoPy) and an overall refactoring of the code via optimized python libraries such as numpy.

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APPENDIX

Appendix A– Resource links (citations can be found in references when necessary)

[1] https://doi.org/10.17632/h3cgnj8hft.1

[2] https://phishstats.info/

[3] https://domcop.com/top-10-million-domains

[4] https://github.com/xanmankey/FishingForPhish.git

[5] https://github.com/xanmankey/PhishAI.git

[6] https://phish-ai.vercel.app/

[7] https://pypi.org/project/FishingForPhish/0.3.0/

[8] https://fishingforphish.readthedocs.io/en/latest/

Figure 1: Example usage of the FishingForPhish module

```python
def main():
   # Initialization
   run = startFishing()
   run.initializeAll()

   fisher = scrape(urlFile="data/urls.txt",
     dataDir="data",
     driver=run.driver,
     classVal=0)

   # Initialization of the page analyzer
   pageData = page()
   fisher.addAnalyzer(pageData)

   # Initialization of the image analyzer
   imageData = image()
   fisher.addAnalyzer(imageData)

   # Once the analyzers have been added, it doesn't matter what
   # instance the goFish method is called with
   fisher.goFish()
   print(pageData.features)
   print(imageData.features)

   # Data Combination
   # The features generated from the other instances are then used
   # when dealing with (creating datasets, classifying, ect.) data
   # Takes the same arguments as the scrape class
   DC = saveFish(urlFile="data/urls.txt",
     dataDir="data",
     driver=run.driver,
     classVal=0,
     analyzers=fisher.analyzers,
     allFeatures=fisher.allFeatures,
     allFeatureNames=fisher.allFeatureNames)
   DC.createDatasets()
   DC.classify()
   print(DC.score)
   print(DC.classifications)

   DC.closePWW3()
   DC.closeSelenium()

if __name__ == "__main__":
   main()
```

Appendix B– Weka visualization examples

Figure 2.1: Matrix of feature versus feature graphs

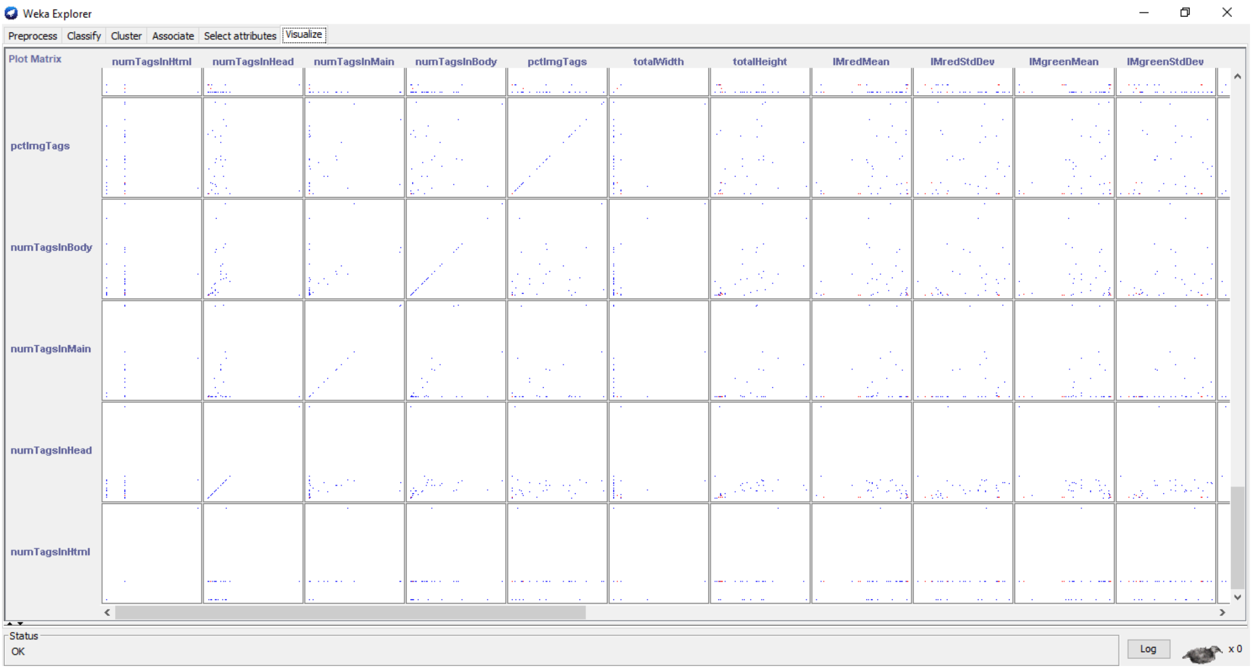

Figure 2,2: Customizing a single Weka graph using customization capabilities

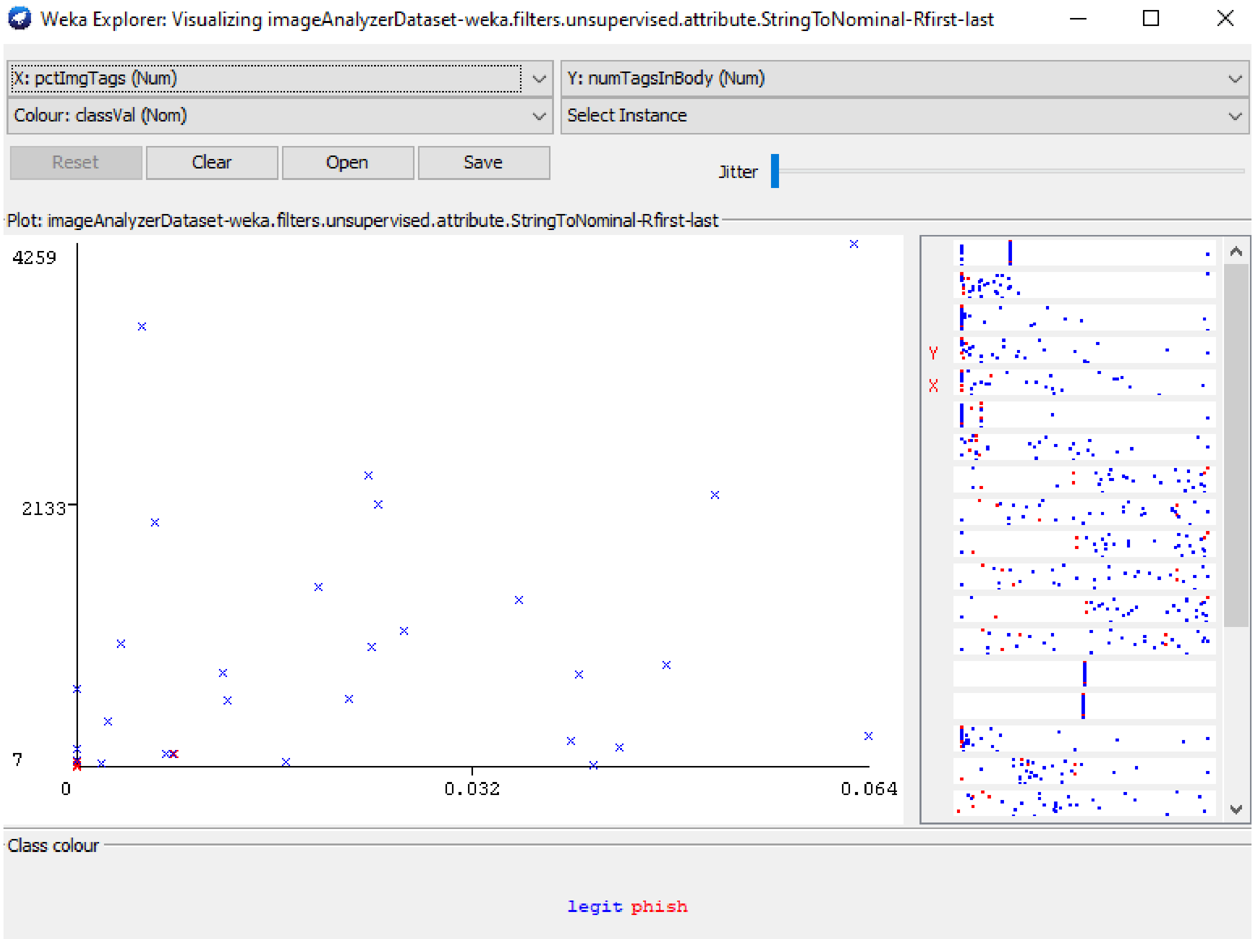

Figure 3: Documented set of image features

1. numTagsInHtml: Number of tags DIRECTLY (does not include nested tags) inside the HTML tag
2. numTagsInHead: Number of tags directly inside the Head tag
3. numTagsInMain: Number of tags directly inside the Main tag
4. numTagsInBody: Number of tags directly inside the Body tag
5. pctImgTags: Percentage of all tags that are image tags
6. totalWidth: Total width of the website (in px)
7. totalHeight: Total height of the website (in px)
8. IMredMean: The mean red value of the full website screenshot
9. IMredStdDev: The mean red standard deviation of the full website screenshot
10. IMgreenMean: The mean green value of the full website screenshot
11. IMgreenStdDev: The mean green standard deviation of the full website screenshot
12. IMblueMean: The mean blue value of the full website screenshot
13. IMblueStdDev: The mean blue value of the full website screenshot
14. IMalphaChannel: A binary; checking if imagemagick identified an alpha channel or not from the full website screenshot.
15. IMgamma: The gamma value of the full website screenshot.
16. numBoldTags: The number of tags that have a font-weight property greater than the normal, 400.
17. averageFontWeight: The total font-weight divided by the number of tags with a font-weight (so all with text).
18. mostUsedFont: The most common font used throughout all tags with the font-family property.
19. averageFontSize: The total font size (in px) divided by the number of tags with the font-size property.
20. numStyles: The number of tags with a font-style or text-decoration value that isn't equal to normal or none.
21. mostUsedStyle: The most common style through all tags with a font-style or text-decoration value that isn't equal to normal or none.
22. pctItalics: The percentage of style tags that have the italic property set.
23. pctUnderline: The percentage of style tags that have the underline property set.

Appendix C– Ranked page features and model output

Figure 4.1: Ranked page feature data

Ranking	**Feature**
1	**ExtMetaScriptLinkRT**
2	**PctExtNullSelfRedirectHyperlinksRT**
3	**NumNumericChars**
4	**PathLength**
5	**PathLevel**
6	**NumAmpersand**
7	**RandomString**
8	**NumQueryComponents**
9	**UrlLength**
10	**HostnameLength**

Figure 4.2: J48 model output (all page features)

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          28               75.6757 %
Incorrectly Classified Instances         9               24.3243 %
Kappa statistic                          0.255
Mean absolute error                      0.2609
Root mean squared error                  0.4744
Relative absolute error                 90.9973 %
Root relative squared error            127.1818 %
Total Number of Instances               37

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.806    0.500    0.893      0.806    0.847      0.263    0.621     0.889     legit
                 0.500    0.194    0.333      0.500    0.400      0.263    0.621     0.311     phish
Weighted Avg.    0.757    0.450    0.802      0.757    0.775      0.263    0.621     0.795

=== Confusion Matrix ===

  a  b   <-- classified as
 25  6 |  a = legit
  3  3 |  b = phish
```

Figure 4.3: Jrip model output (all page features)

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          30               81.0811 %
Incorrectly Classified Instances         7               18.9189 %
Kappa statistic                          0.3476
Mean absolute error                      0.1961
Root mean squared error                  0.3801
Relative absolute error                 68.4062 %
Root relative squared error            101.8873 %
Total Number of Instances               37

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.871    0.500    0.900      0.871    0.885      0.349    0.624     0.873     legit
                 0.500    0.129    0.429      0.500    0.462      0.349    0.624     0.312     phish
Weighted Avg.    0.811    0.440    0.824      0.811    0.817      0.349    0.624     0.782

=== Confusion Matrix ===

  a  b   <-- classified as
 27  4 |  a = legit
  3  3 |  b = phish
```

Figure 4.4: Naive Bayes model output (all page features)

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          32               86.4865 %
Incorrectly Classified Instances         5               13.5135 %
Kappa statistic                          0.5861
Mean absolute error                      0.1353
Root mean squared error                  0.3676
Relative absolute error                 47.2011 %
Root relative squared error             98.5466 %
Total Number of Instances               37

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.871    0.167    0.964      0.871    0.915      0.605    0.860     0.953     legit
                 0.833    0.129    0.556      0.833    0.667      0.605    0.909     0.758     phish
Weighted Avg.    0.865    0.161    0.898      0.865    0.875      0.605    0.868     0.921

=== Confusion Matrix ===

  a  b   <-- classified as
 27  4 |  a = legit
  1  5 |  b = phish
```

Appendix D– Ranked image features and model output

Figure 5.1: Ranked image feature data

1	**mostUsedFont**
2	**averageFontSize**
3	**numBoldTags**
4	**favicon**
5	**numTagsInMain**
6	**pctImgTags**
7	**IMgreenMean**
8	**IMredMean**
9	**pctUnderline**
10	**IMblueStdDev**

Figure 5.2: J48 model output (all image features)

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          28               75.6757 %
Incorrectly Classified Instances         9               24.3243 %
Kappa statistic                          0.255
Mean absolute error                      0.2609
Root mean squared error                  0.4744
Relative absolute error                 90.9973 %
Root relative squared error            127.1818 %
Total Number of Instances               37

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.806    0.500    0.893      0.806    0.847      0.263    0.621     0.889     legit
                 0.500    0.194    0.333      0.500    0.400      0.263    0.621     0.311     phish
Weighted Avg.    0.757    0.450    0.802      0.757    0.775      0.263    0.621     0.795

=== Confusion Matrix ===

  a  b   <-- classified as
 25  6 |  a = legit
  3  3 |  b = phish
```

Figure 5.3: Jrip model output (all image features)

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          30               81.0811 %
Incorrectly Classified Instances         7               18.9189 %
Kappa statistic                          0.3476
Mean absolute error                      0.1961
Root mean squared error                  0.3801
Relative absolute error                 68.4062 %
Root relative squared error            101.8873 %
Total Number of Instances               37

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.871    0.500    0.900      0.871    0.885      0.349    0.624     0.873     legit
                 0.500    0.129    0.429      0.500    0.462      0.349    0.624     0.312     phish
Weighted Avg.    0.811    0.440    0.824      0.811    0.817      0.349    0.624     0.782

=== Confusion Matrix ===

  a  b   <-- classified as
 27  4 |  a = legit
  3  3 |  b = phish
```

Figure 5.4: Naive Bayes model output (all image features)

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          32               86.4865 %
Incorrectly Classified Instances         5               13.5135 %
Kappa statistic                          0.5861
Mean absolute error                      0.1353
Root mean squared error                  0.3676
Relative absolute error                 47.2011 %
Root relative squared error             98.5466 %
Total Number of Instances               37

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.871    0.167    0.964      0.871    0.915      0.605    0.860     0.953     legit
                 0.833    0.129    0.556      0.833    0.667      0.605    0.909     0.758     phish
Weighted Avg.    0.865    0.161    0.898      0.865    0.875      0.605    0.868     0.921

=== Confusion Matrix ===

  a  b   <-- classified as
 27  4 |  a = legit
  1  5 |  b = phish
```

Appendix F– Combined ranked features and model output

Figure 6.1: Combined ranked feature data

1	**averageFontSize**
2	**mostUsedFont**
3	**numBoldTags**
4	**NumDots**
5	**PathLevel**
6	**mostUsedStyle**
7	**favicon**
8	**UrlLength**
9	**pctUnderline**
10	**totalHeight**

Figure 6.2: J48 model output (all features)

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          30               81.0811 %
Incorrectly Classified Instances         7               18.9189 %
Kappa statistic                          0.3476
Mean absolute error                      0.1881
Root mean squared error                  0.4326
Relative absolute error                 65.6285 %
Root relative squared error            115.964  %
Total Number of Instances               37

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.871    0.500    0.900      0.871    0.885      0.349    0.852     0.954     legit
                 0.500    0.129    0.429      0.500    0.462      0.349    0.866     0.571     phish
Weighted Avg.    0.811    0.440    0.824      0.811    0.817      0.349    0.854     0.892

=== Confusion Matrix ===

  a  b   <-- classified as
 27  4 |  a = legit
  3  3 |  b = phish
```

Figure 6.3: Jrip model output (all features)

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          32               86.4865 %
Incorrectly Classified Instances         5               13.5135 %
Kappa statistic                          0.4669
Mean absolute error                      0.1389
Root mean squared error                  0.3604
Relative absolute error                 48.4384 %
Root relative squared error             96.607  %
Total Number of Instances               37

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.935    0.500    0.906      0.935    0.921      0.470    0.895     0.968     legit
                 0.500    0.065    0.600      0.500    0.545      0.470    0.895     0.500     phish
Weighted Avg.    0.865    0.429    0.857      0.865    0.860      0.470    0.895     0.892

=== Confusion Matrix ===

  a  b   <-- classified as
 29  2 |  a = legit
  3  3 |  b = phish
```

Figure 6.4: Naive Bayes model output (all features)

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          31               83.7838 %
Incorrectly Classified Instances         6               16.2162 %
Kappa statistic                          0.4739
Mean absolute error                      0.1673
Root mean squared error                  0.3404
Relative absolute error                 58.3459 %
Root relative squared error             91.2543 %
Total Number of Instances               37

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.871    0.333    0.931      0.871    0.900      0.481    0.758     0.915     legit
                 0.667    0.129    0.500      0.667    0.571      0.481    0.758     0.510     phish
Weighted Avg.    0.838    0.300    0.861      0.838    0.847      0.481    0.758     0.850

=== Confusion Matrix ===

  a  b   <-- classified as
 27  4 |  a = legit
  2  4 |  b = phish
```