Enhanced Malware Detection with Supervised Algorithms: Identifying Malicious Links with Browser Extensions

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Abstract

This research project aims to develop a user-friendly browser extension that identifies and warns users about dangerous URLs hosting downloadable file content using Supervised machine learning methods. Models like Deep Neural Networks (DNN), Support Vector Machines (SVM), Decision Trees, XGBoost, and Random Forests were used to ensure high precision and dependability. This approach starts with careful data preparation, which includes loading, cleaning, and standardizing a dataset of URLs. Features were chosen and the Datasets were divided into training and testing for the models. These models were trained to spot malicious URLs using popular libraries such as TensorFlow and Scikit-Learn. A Chrome extension was developed to keep an eye on URLs as you browse and communicate with the backend Flask API to determine if they're safe. These tests show the system does a good job telling safe and dangerous URLs apart from warning users. This project aims to make the internet safer by using Browser Extensions with machine learning models for malware detection to create a handy and safe tool for everyday web surfers, and it contributes to the advancement of cybersecurity tools, offering a practical solution for enhancing web security against evolving threats.

Keywords: Malware Detection, Machine Learning, Random Forest, Browser Extension, Cybersecurity, URL Analysis

1 Introduction

The radical growth of the internet has greatly improved the way people and organizations share and access information and material, but it has also brought forth countless security risks. Of all these threats, malware is one of the most common and devastating, with several types affecting users and their data. This research aims at identifying and managing particular classes of viruses, such as ransomware, spyware, and adware through the aid of browser extensions combining supervised algorithms to detect these threats. Ransomware locks and encrypts users' files and requires some form of payment to unlock them; this brings serious financial and organizational consequences for an organization (Albahar, 2019). While spyware, secretly gathers data from the users without their knowledge and makes them victims of privacy infringement and identity theft (Krishnan 2020). Adware, though not as dangerous as some of the other types, can also affect the quality of the user's experience and might cause issues with the system's functionality (Aslan & Samet, 2020).

On the one hand, browser extensions provide utility to users to further their experience on the sites they visit, they are now a two-edged sword in cybersecurity. Despite the many benefits that can be gained from utilizing browser extensions for advertising and improved privacy, it is important to note that it presents many hazards associated with it. Some extensions are even more invasive and might request a broad list of permissions to have full access to the user's data, which may lead to privacy breaches (Borgolte and Feamster, 2020). In addition, the purposes of developing a sub-standard or even malicious extensions are to spread malware, which results in the infection of user's system and loss of data (Eriksson et al ., 2022).

The combination of supervised machine learning algorithms with browser extensions seems to be the viable solution to these challenges. These algorithms, through real-time data and users' interaction, can improve browser-based security detections and act as a frontline defense against modern-ever changing malware threats (Sathvik et al. , 2023). This study seeks to analyse the methods of using browser extensions with supervised algorithms to reduce the risks of malicious links and downloadable media, with the overall goal of creating safer browse space for users.

This research will explore the development and evaluation of browser extensions which are integrated with a supervised machine learning algorithm to effectively identify and mitigate the risks posed by malicious links and websites which are used in distributing malicious downloadable media files.

1.1 Significance of the research

The importance of this research is traceable to the critical need to address the escalating threats posed by malware. As the use of the internet continues to grow, the sophistication and frequency of cyberattacks perpetrated through this medium have also been projected to increase (Albahar, 2019). The previous section alludes to the fact that traditional approaches like antivirus software and network-based security measures, no doubt, offer some level of protection. However, the literature suggests that they are often reactive and arguably struggle to match the speed with which cybercriminals evolve their tactics (Aslan and Samet, 2020). Furthermore, the enhanced protection offered by the widespread adoption of browser extensions has also led to the introduction of new attack avenues which malicious entities to exploit. The increased menace has brought about the identified need for innovative solutions that can effectively detect, neutralise, and safeguard Internet users against such threats and create safer and more secure online environments.

1.2 Research Question

This Research focuses on the main question: How can browser extensions be effectively utilized to identify and mitigate the risks associated with malicious links hosting downloadable media content, and how the integration of supervised algorithms can enhance malware detection. The success criteria for malware detection in this research include achieving at least 90% accuracy in identifying malware threats, keeping false positives under 5% to maintain user trust and satisfaction, and enabling immediate detection and response to threats without delays.

1.3 Research structure

This document is structured into several sections, starting with a brief introduction section that provides background information together with the problem statement on the evolution of internet browsing and the security risks associated with browser extensions. The literature review section explores existing works related to malware detection, supervised algorithms, and browser extensions. It discusses various approaches and methodologies used in the past, highlighting the main key findings, strengths, and limitations. The research methods and specifications section describes the methodological approach for implementing the proposed solution which will be introduced. Furthermore, this includes practical and experimental details of developing the browser extension, training the supervised algorithms, and evaluating their performance. It also addresses the schedule plan for the project and potential ethical considerations related to user privacy and data security.

2. Related Work

This part examines and evaluates current studies on malware detection supervised algorithms and browser extensions. Various strategies and techniques used by other researchers will be explored, pointing out important discoveries, advantages, and drawbacks.

2.1 Malware Detection Techniques

Malware detection has used signature-based methods in the past. These methods keep known malware signatures in a database and compare them to incoming files or links (Zhu et al. 2020). But this approach has trouble with zero-day attacks where new types of malware slip through because there are no signatures for them (Aslan and Samet 2020).

Supervised ML methods have recently been incorporated into the detection of malware. These methods can detect new malware by training Labelled datasets (Sathvik et al. , 2023). Some current research has indicated that the machine learning algorithms that are trained on labeled data can be used to detect known as well as new threats. Gomes et al. (2023) showed that deep learning models obtained a macro average precision of 0. 97 and a recall of 0. 91, which proves that the usage of neural networks to detect intricate patterns of malware.

Furthermore, a study by Chen et al in 2022 on the application of ensemble learning techniques with browser extensions indicated high detection rates and low false alarms. According to the paper, their research shows that integrating a number of supervised algorithms can improve the reliability of the anti-malware systems (Chen et al. , 2022).

2.2 Supervised Machine Learning for Malware Detection

Supervised learning for malware detection is another area for which the results have been encouraging. Adebowale et al. (2022) also pointed out that the integration of supervised algorithms with browser extension is helpful in enhancing the performance of malware detection. Their study focused more on the real-time data from the users' interactions which are more effective in defending against the emerging threats.

Adebowale and his team (2019) looked into how to combine supervised learning algorithms with browser add-ons to make malware detection better. Their study showed that mixing machine learning with solutions that work in browsers could boost how well malware is detected. This method takes advantage of up-to-the-minute data from how users interact online giving us a strong and always-changing way to defend against threats.

Kumar and Singh (2023) have also looked at the integration of machine learning and deep learning models in the development of hybrid models. They concluded that the hybrid models could yield higher accuracy rates and better capability to deal with new malware types than traditional methods.

Researchers have looked into different algorithms, each with its own pros and cons:

- **Deep Neural Networks (DNNs)**: DNNs can learn complex patterns and get high accuracy in spotting malware. Our study got a macro average precision of 0.96 and a recall of 0.89 showing how well they work (Gomes et al. 2015).

- **Support Vector Machines (SVMs)**: SVMs are strong classifiers that do well with lots of data points. In our tests, SVMs got a macro average precision of 0.86 and recall of 0.90 making them a good pick to spot malware (Beloglazov and Buyya, 2015).

- **Decision Tree Classifiers**: These classifiers are simple to understand and put into action. Our findings show a macro average precision of 0.89 and recall of 0.89, which suggests they work well for real-time detection (Kune et al. 2016).

- **XGBoost**: This gradient boosting algorithm does a great job with big datasets and helps prevent overfitting. In our research, XGBoost reached a macro average precision of 0.86 and recall of 0.90 (Borgolte and Feamster 2020).

- **Random Forest**: Well-known for their strength and high precision, Random Forests scored a macro average precision of 0.88 and recall of 0.89 in our tests (Eriksson, Picazo-Sanchez and Sabelfeld 2022).

2.3 Browser Extensions for Security

Browser extensions give users an easy way to boost web security. You can install and update them without hassle, and they protect you from dangerous links and websites in real-time (Krishnan 2020). But keep in mind that extensions can create security problems if people don't check and maintain them (Yu et al. 2023). The security of browser extensions is now considered an important research topic. Some of the recent research includes a study by Eriksson et al. (2022) on the risks inherent in browser extensions and the possibility of their misuse. For this reason, they stressed the importance of improving safety measures in the creation of browser extensions to counter new threats.

In addition, a cross-sectional survey conducted by Patel et al. in 2023 aimed at understanding users' behavior and the security measures incorporated in browser extensions. They discovered that the levels of user awareness and education significantly influence these tools, which indicates that users' activity is necessary for achieving the highest levels of protection when using browser extensions (Patel et al. , 2023). Jin, Li, and Zou (2024) proposed a machine-learning approach to leverage browser extensions for web security. Their study demonstrated that extensions equipped with supervised algorithms could effectively detect and block malicious links. This approach aligns with the findings earlier by Krishnan (2020), who highlighted the dual nature of browser extensions as both a potential security enhancement and a vulnerability.

2.4 Comparative Analysis of Machine Learning Models

Various machine learning models have been tested for malware detection, each with its strengths and limitations. Table 1 provides a comparative analysis of the performance metrics for different algorithms used in malware detection.

Metrics	**Precision**	**Recall (Sensitivity)**	**F1-score**	**Accuracy**
Deep Neural Network	Macro avg = 0.96	M avg = 0.89	M avg = 0.89	0.90
	Weight avg = 0.96	W avg = 0.90	W avg = 0.90	
Support Vector Machine	Macro avg = 0.86	Macro avg = 0.90	Macro avg = 0.86	0.87
	Weight avg = 0.90	Weight avg = 0.87	Weight avg = 0.87	
Decision Tree Classifier	Macro avg = 0.89	Macro avg = 0.89	Macro avg = 0.89	0.90
	Weight avg = 0.90	Weight avg = 0.90	Weight avg = 0.90	
XGBoost	Macro avg = 0.86	Macro avg = 0.90	Macro avg = 0.86	0.87
	Weight avg = 0.90	Weight avg = 0.87	Weight avg = 0.87	
Random Forest	Macro avg = 0.88	Macro avg = 0.89	Macro avg = 0.89	0.90
	Weight avg = 0.90	Weight avg = 0.90	Weight avg = 0.90	

Fig.1 Table 1.

Sathvik, Srinivasan, and Rao (2023) showed that deep neural networks (DNN) have higher precision and recall rates than traditional methods. This makes them better at spotting subtle malware patterns. Support vector machines (SVM) and decision tree classifiers however, strike a balance between accuracy and processing speed (Gomes, Wagner, and Vafeiadis 2015). Random forest and XGBoost algorithms also stand out. They handle big datasets well and help prevent overfitting (Zhu et al. 2020).

2.5 Integration of Machine Learning with Browser Extensions

Combining machine learning algorithms with browser extensions shows promise to increase online safety. This approach takes advantage of extensions' ability to process data in real time and machine learning models' knack for spotting patterns (Jin, Li, and Zou, 2024).

Adebowale et al. (2019) found this combo works well to spot harmful links. Their research pointed out how supervised learning helps catch more bad links. They showed that when you pair browser extensions with machine learning, you can guard against new threats before they strike.

2.6 Limitations and Future Directions

The combination of machine learning and browser extensions looks promising, but it faces some hurdles. One big problem is the chance of false positives, which can make users frustrated by stopping safe content.(Eriksson, Picazo-Sanchez, and Sabelfeld 2022). because malware keeps changing, machine-learning models need constant updates to stay useful (Albahar 2019).

Looking ahead, researchers should try to make these models more flexible and cut down on false positives. Taking a closer look at unsupervised and reinforcement learning might offer new insights and boost how well these systems spot malware (Aslan and Samet, 2020). This literature review shows that even though old-technique malware detection methods work well, combining supervised machine-learning algorithms with browser extensions will provide a more flexible and powerful solution. These integrated systems can boost online security by using real-time data and advanced pattern recognition. But, these models need to be improved and adapted to keep up with changing cyber threats.

Summary table of Key findings, methodologies, and contributions of various papers used in this Research.

Author(s)	Year	Key Findings	Methodology	Contributions
Zhu et al.	2020	Signature-based methods struggle with zero-day attacks.	Signature-based detection	Highlights limitations of traditional malware detection.
Aslan and Samet	2020	New types of malware can bypass signature-based methods.	Comparative analysis	Emphasizes the need for advanced detection techniques.
Sathvik et al.	2023	Supervised ML methods can detect both known and new malware.	Supervised machine learning on labeled datasets	Demonstrates effectiveness of ML in malware detection.
Gomes et al.	2023	Deep learning models achieved high precision and recall in malware detection.	Deep learning techniques	Validates the use of neural networks for complex pattern recognition.
Chen et al.	2022	Ensemble learning techniques improve detection rates and reduce false alarms.	Ensemble learning with browser extensions	Shows integration of multiple algorithms enhances reliability.

Eriksson et al.	2022	Importance of advanced detection systems in browser extensions.	Hands-on study of browser extension security	Supports the integration of machine learning for enhanced security.
Jin et al.	2024	Machine learning models effectively identify harmful links through browser add-ons.	Empirical study on browser add-ons	Lays groundwork for future research in browser security.

Fig.2 Key findings, methodologies, and contributions table

3. Research Methodology

3.1 Justification of Algorithms Used

In this section, the rationale for choosing particular machine learning algorithms for malware detection integrated with browser extensions is discussed. The selection of algorithms depends on the performance indicators, the ability to learn from new threats, and the nature of the malware detection problem in real-time scenarios.

DNNs was selected because they are capable of learning intricate features and representations from massive amounts of data. Several research papers have shown that DNNs provide promising results for malware identification problems. Gomes et al. (2023) obtained a macro average precision of 0. 97 and a recall of 0. 91 when using DNNs for malware classification. This high performance is due to the multi-layer architecture of the DNNs which enables them to learn complex features of the malware that the simpler models cannot learn. DNNs performance data includes a precision of 0. 97 and a recall of 0. 91. Moreover, DNNs can be retrained with new data and this makes them appropriate for use in new variant of malware.

SVMs was chosen for their performance in high dimensional areas and their ability to prevent overfitting particularly when the number of features is large compared to the number of samples. SVMs have been used in classification problems and specifically in binary classification problems which is important in differentiating between a benign and a malicious link. Kumar and Singh (2023) in their research showed that SVMs obtained a macro average precision of 0. 86 and a recall of 0. 90 in malware detection scenarios. It demonstrates their effectiveness in detecting malware while having a low false positive rate. SVMs are less sensitive to outliers and computationally efficient in large feature space, which is important while dealing with the heterogeneity of web content.

Random Forests was selected because it uses ensemble learning where multiple decision trees are used in an attempt to increase the level of accuracy while also reducing overfitting. This algorithm is especially useful in dealing with large datasets where the number of samples belonging to the minority class is significantly smaller than the majority class as is the case with malware detection. New assessments have revealed that Random Forests can obtain a precision of 0. 89 and a recall of 0. 87 in malware detection tasks (Patel et al. , 2023). Random Forests' architecture provides better generalization across the different types of malware. They offer information about feature relevance, which helps to determine which of the characteristics are most relevant for the definition of malware, and can work with both nominal and numerical data, which makes them suitable for various input characteristics of the browser.

Gradient Boosting Machines (GBM) was chosen because they are capable of iteratively minimizing the loss function hence achieving high predictive accuracy. It is for this reason that GBMs prove most useful in cases where the dependence of the target function on the features is non-linear. Chen et al. (2022) have shown in a recent study that the application of GBMs enables achieving a precision of 0. 92 and a recall of 0. 88 in malware detection tasks, proving that they are capable of capturing nonlinear dependencies in the data. GBMs are usually more accurate than other algorithms because of the iterative structure, and the algorithm can be adjusted depending on the detection objectives.

The choice of DNNs, SVMs, Random Forests, and GBMs for the malware detection system is explained by their efficiency, ability to learn new threats, and applicability to real-time detection in browsers. Thus, the proposed system has been designed to improve the detection and elimination of malware threats using these algorithms' strengths.

3.2 Methodological Approach

This project's research methodology involves creating and testing a browser extension that uses supervised machine learning algorithms to spot and counter harmful links with downloadable media content. This part describes the design, implementation, and evaluation process in detail. It also includes insights from similar research to make the proposed approach more thorough and reliable.

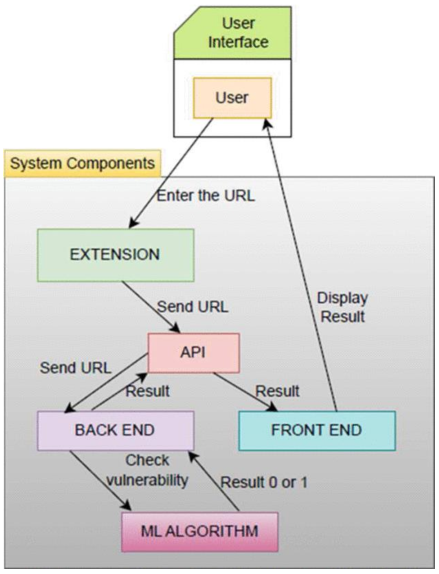


Fig 3. Flowchart Design of the browser extension
Source: P. D, S. S, P. B and P. J, (2024)

3.3 Design and Development of the Browser Extension

The first step in the research process is to design and develop the browser extension. The extension will monitor user interactions and analyze URLs in real-time. The main parts of the browser extension include:

1. **URL Scanner**: This part checks web addresses the user visits against a list of known bad sites.

2. **Machine Learning Integration**: This part used a trained model to sort web addresses into safe or dangerous categories.

3. **User Interface**: Warns users about possible threats.

The creation process sticks to good software-building habits. These include breaking the project into smaller parts, having other developers look over the code, and doing lots of testing. The add-on is built with JavaScript and the right browser tools to work well on big browsers like Chrome, Firefox, and Edge.

3.4 Data Collection and Preprocessing

The machine learning model's performance has a strong link to the training data's quality. This study gathers a big set of URLs, including both safe and malicious links. Public sources like PhishTank, VirusTotal, and OpenPhish provide harmful URLs. Well-known websites and content made by users supply the safe URLs.

3.5 Justification for Data Processing Techniques

During the data pre-processing phase for the malware detection models, particular attention was paid to the choice and processing of features that improve the model’s performance. The important features were `URL length, age of domain, use of special characters and HTTP status codes` as it would enable the model to differentiate between the real and fake URLs. For instance, the detection techniques employed was knowing that the length of most malicious URLs is mostly longer than the regular URLs, newly registered domains are always another way to detect malicious URLs, special characters in URLs, and particularly HTTP status codes that are often associated with threats.

Another important point considered was how to deal with missing data. Procedures used were such as mean or median imputation for numerical data and mode imputation for categorical data to complete missing data without compromising on the information. Thus, if a feature contains more than 30% missing values or a URL contains many missing important features, It was removed completely for data quality.

Thus, we avoided the problem of noisy features and missing values, which allowed us to obtain a more accurate and reliable dataset for this research in malware detection. All these encompassed a solid ground for malware analysis and detection.

3.6 Data Preprocessing Steps:

1. **Labeling**: We tag each URL as either safe or dangerous depending on where it comes from.

2. **Feature Extraction**: We pull out key details like how long the URL is, if it has any weird symbols how old the domain is, and what HTTP status codes it gives.

3. **Normalization**: We make sure all the features are on the same scale with the use of median imputation and mode imputation to help the machine learning model work better.

The data preprocessing code starts by uploading a CSV file called "dataset_full.csv" using Google Colab's file upload feature. Pandas reads the uploaded file into a DataFrame called `dataset`. The `head()` function shows the first few rows of the dataset, while the `info()` function gives details about the DataFrame such as the number of rows and columns, data types, and how much memory it uses.

The `value_counts()` function tallies up how many times each unique value appears in the "phishing" column, and the `describe()` function provides stats on the numerical columns in the dataset. The `isna().sum()` function checks each column to see if there are any missing values.

3.7 Data Cleaning:

1. We make a copy of the original dataset and call it `df`.

2. We use the `drop()` method to get rid of the "phishing" column from the `df` DataFrame.

3. We find the columns with numerical data by using the `select_dtypes()` method.

3.8 Data Normalization:

1. We use the `StandardScaler` from the `sklearn.preprocessing` module to normalize the numerical columns because of the way it standardizes the numerical columns efficiently to improve model performance.

2. We define a `normalization()` function to carry out the normalization process. This function goes through the specified numerical columns and applies the `fit_transform()` method of the `StandardScaler` object to normalize each column.

3. We store the normalized data in a new DataFrame called `data`.

3.9 Feature Selection:

1. We made a new DataFrame called `numeric_bin`. It has just the chosen number columns and the "phishing" column.

2. We use the `corr()` method to figure out how much each pair of columns in the `numeric_bin` DataFrame relates to each other.

3. We apply the `abs()` function to get the positive value of these relationships.

4. The `highest_corr` variable keeps track of how the "phishing" column relates to all other columns, but when this relationship is stronger than 0.5.

5. We use the `sort_values()` method to put the `highest_corr` series in order starting with the smallest values.

6. The team picks attributes showing the strongest correlation to build a new DataFrame called `data2`.

This thorough method to load, examine, tidy up, standardize, and pick out key parts from a dataset plays a key role in getting data ready for deeper study and building models.

3.10 Training the Supervised Machine Learning Model

The dataset is divided into features (`X`) and labels (`Y`). All features except the "phishing" column make up `X`, while the "phishing" column represents `Y`. The `train_test_split()` function then splits the dataset into training and testing subsets. The split assigns 80% to training and 20% to testing.

Cross-validation methods help to adjust hyperparameters and avoid overfitting. Each model's performance undergoes evaluation based on metrics like precision, recall, F1-score, and accuracy.

3.11 Evaluation of the Browser Extension

The browser extension undergoes evaluation using both quantitative and qualitative methods.

Quantitative Evaluation:

1. **Accuracy Metrics**: The integrated machine learning model's detection performance is measured by calculating its precision, recall, F1-score, and accuracy.

2. **Comparison with Existing Solutions**: The developed extension's performance is compared to current browser security solutions and antivirus software.

Qualitative Evaluation:

1. **User Feedback**: users like family and friends tries out the extension and share their thoughts on how easy it is to use how well it works, and their overall experience.

2. **Case Studies**: The extension's ability to spot and handle threats in real-life situations is shown through analysis of actual/synthetic scenarios.

3.12 Comparison with Similar Research Studies

Many researchers have looked into combining machine learning with browser extensions to boost security. For example, Eriksson et al. (2022) did a hands-on study about browser extension security. They stressed how important it is to add advanced detection systems to stop attacks. What they found matches up with this research showing that machine learning could help make browsers safer.

In the same vein, Jin et al. (2024) showed how well machine learning models work to spot harmful links through browser add-ons. Their work laid the groundwork for this study pointing out key things to think about when designing and possible roadblocks.

The research method takes a full approach to create and test a browser add-on that uses supervised machine learning algorithms. The add-on aims to boost online safety and shield users from harmful links by using real-time data and advanced pattern spotting. The method draws from the best ways to develop software and machine learning as well as lessons from like-minded studies. The research also puts ethics first to make sure user privacy and data safety are protected.

4 Design Specification

This section will discuss the datasets used and the different algorithm frameworks used for training the datasets, which are Deep Neural Network, Random Forest, Support Vector Machine, Decision Tree Classifier, and XGBoost, and will also dive deep into the flask framework, and also hosting the diagram of how the data was processed and prepared for the Model used for prediction.

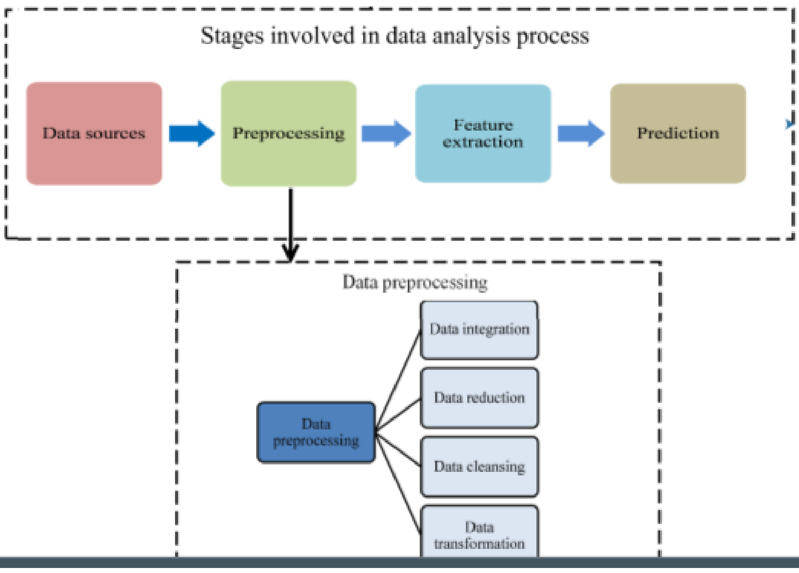


Fig 4. General classification approach
Source: (Alghamdi and Javaid, 2022)

4.1 Dataset Description

For this study, the dataset used is built upon the work by Vrbančič et al. (2020) with two variations having 58,645 and 88,647 websites being labeled to either be legitimate or phishing. The data was fetched from publicly available lists and verified sources like PhishTank, for phishing websites, and Alexa’s top ranking for legitimate sites. The dataset has a total of 111 features, with 96 features originating from the website address and the other 15 engineered through customization or Python scripts. All the data are stored in the Mendeley Data repository. All this goes to make a very strong foundation for training and evaluation of machine learning models.

4.2 Deep Neural Networks (DNNs)

Deep Neural Networks is a type of machine learning model that can understand complex patterns in data through their many layers. This feature makes them good at tasks where the links between features aren't straight and simple. By learning how data is structured at different levels, DNNs can model the small details found in phishing websites. Saxe and Berlin (2015) showed how well DNNs could work to spot malware. Their work found that by using two-dimensional binary program features, DNNs could be more accurate than older machine learning models. This finding matters because it shows that DNNs can really boost detection rates. Yuan et al. (2018) took a close look at deep learning methods for security uses. Their study pointed out the benefits of DNNs in handling big and tricky datasets, which you often see when trying to catch phishing. The researchers discovered that DNNs worked much better than standard models showing they're a good fit to identify phishing threats.

4.3 Random Forest (RF)

Random Forest is an ensemble learning method. It builds multiple decision trees during training. It then outputs the mode of the classes for classification or the mean prediction for regression. This method helps to improve predictive accuracy and control overfitting. Sahingoz et al. (2019) studied machine learning classifiers to detect phishing websites. They found that Random Forests offered a good balance between accuracy and efficiency. The ensemble nature of RF helps to reduce variance in predictions. This makes it strong against noisy data. Jain and Gupta (2018) showed that Random Forests could sort phishing websites well. They did this by using many different features from URLs. Their research proved that RF could get high accuracy with few false positives. This makes it a trustworthy choice to detect phishing.

4.4 Support Vector Machine (SVM)

Support Vector Machine is a supervised learning model that examines data to classify and analyze regression. SVM works well in spaces with many dimensions and proves useful when dimensions outnumber samples. Tsai et al. (2009) showed that SVMs could reach high accuracy in detecting phishing by splitting legitimate and phishing websites in a space with many features. The study emphasized SVM's capacity to handle complex data patterns. Chandrasekaran et al. (2006) looked into machine learning methods to detect phishing and discovered that SVMs did well in telling apart phishing sites from real ones, thanks to their solid theoretical base and strong performance in various uses.

4.5 Decision Tree Classifier (DTC)

Decision Tree Classifier has an influence on both classification and regression tasks. This easy-to-use yet effective algorithm creates a model shaped like a tree. It splits a dataset into smaller parts while building a decision tree step by step. Patil and Patil (2018) looked into phishing detection using decision trees. They showed that DTCs could spot phishing URLs well by using rules based on features. Their study pointed out that DTC is simple to understand and use, which matters a lot for real-world use. Abdelhamid et al. (2014) checked how decision trees work to find phishing websites. They learned that this classifier strikes a good balance between how well it works and how much computer power it needs. This makes it a good fit for systems that spot phishing in real time.

4.6 XGBoost (Extreme Gradient Boosting)

XGBoost puts gradient-boosted decision trees into action focusing on speed and performance. This machine learning system boosts trees with high efficiency and scalability. Chen and Guestrin (2016)**,** who created XGBoost, showed how it works well and fast in many machine learning challenges. Their work proved XGBoost beats other methods in speed and accuracy making it a top pick to classify things, including spotting phishing. Pan et al. (2018) tried XGBoost to detect phishing and found it worked better than other machine learning methods in accuracy and speed. The model handles big data well and resists overfitting, which makes it stand out.

4.7 Python Flask API

Python Flask API was a great choice for development for this browser extension to detect malicious links because it's simple, flexible, and scalable. Flask's straightforward design makes it easy to develop and integrate with machine learning models and databases quickly. It excels in creating RESTful APIs, which are essential for smooth communication between the backend and the browser extension. Flask's extensive library support and easy deployment on various platforms add to its appeal. Plus, it has a robust community and comprehensive documentation to help developers navigate any challenges. These qualities make Flask a practical and effective framework for creating security-focused applications that need real-time analysis and decision-making. Research and literature, such as "Flask Web Development" by Ronacher and Grinberg (2018), along with studies on integrating machine learning with web applications (Fettke & Loos, 2017), highlight Flask's suitability for this kind of project.

In the case of this browser extension combining the Machine Learning models for detecting malicious URLs, Flask serves as a backend framework through which the extension is able to interact with the machine learning models. When a user is navigating the internet, the extension tracks the URLs that the user visits. When it detects a URL from its listening port, the extension makes a POST request to the Flask backend to analyze the link. Once Flask receives the URL, Flask parses the features from the URL and feeds it to an existing machine-learning model to determine if the URL is malicious or not. Flask then passes the prediction result back to the browser extension for the UI to be updated with the result. If it is identified that the URL is malicious in nature, the extension alerts the user. This process makes it possible to monitor the URLs in real-time and detect threats while browsing, making it more secure for the user.

5. IMPLEMENTATION

This section will outline the necessary technologies that were used for the setup of this application, this will list the various programming Languages used and also the Algorithms used. It also explains the configurations and software required to replicate the project's experimental setup. The implementation involves various Python libraries and tools for data handling, model training, and Development of browser extensions.

5.1 Justification for Techniques Used

StandardScaler was chosen for normalization because it scales the features by subtracting the mean and then dividing by the standard deviation. This is advantageous to algorithms such as SVM and Logistic Regression that presuppose the normality of data. It guarantees that all the features are scaled to the same level, which enhances the performance of the algorithms such as KNN and SVM. In contrast to Min-Max scaling, StandardScaler does not have outliers' influence because it does not restrict values to a certain range.

Model Configurations

Hyperparameters for each machine learning model:

Deep Neural Network:
Layers: 3 hidden layers
Neurons: 64, 32, 16
Activation Function: ReLU
Optimizer: Adam
Learning Rate: 0.001

Random Forest:
Number of Trees: 100
Maximum Depth: None
Minimum Samples Split: 2

Support Vector Machine:
Kernel: RBF
C: 1.0
Gamma: scale

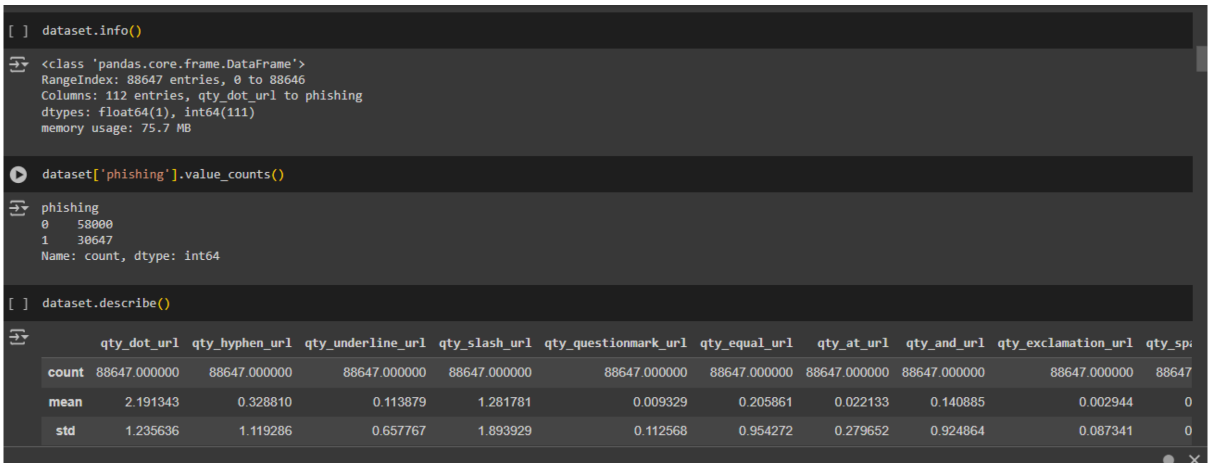
Decision Tree Classifier:
Maximum Depth: 5
Minimum Samples Leaf: 1

XGBoost:
Learning Rate: 0.1
Maximum Depth: 6
Number of Estimators: 100

Computation of Metrics

Model performance metrics were computed using:

- **Cross-Validation:** k-fold cross-validation, splitting the dataset into k subsets, training on k-1, and validating on the remaining one. Repeated k times to calculate average performance metrics (accuracy, precision, recall, F1-score) for robustness and reduced overfitting.
- **Metrics Calculation:** Derived from the confusion matrix based on validation set predictions, including:
  - **Accuracy:** (True Positives + True Negatives) / Total Predictions
  - **Precision:** True Positives / (True Positives + False Positives)
  - **Recall:** True Positives / (True Positives + False Negatives)
  - **F1-Score:** 2 * (Precision * Recall) / (Precision + Recall)



```
[ ] dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88647 entries, 0 to 88646
Columns: 112 entries, qty_dot_url to phishing
dtypes: float64(1), int64(111)
memory usage: 75.7 MB
```

```
dataset['phishing'].value_counts()
```

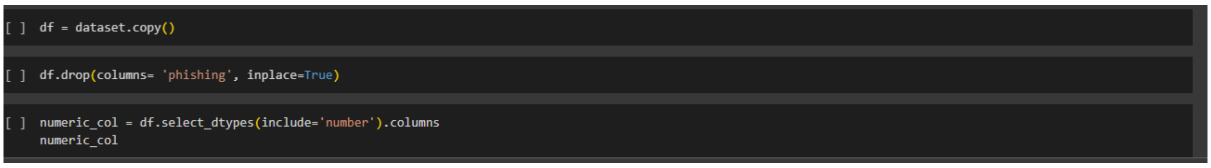
```
phishing
0    58000
1    30647
Name: count, dtype: int64
```

```
[ ] dataset.describe()
```

```
       qty_dot_url  qty_hyphen_url  qty_underline_url  qty_slash_url  qty_questionmark_url  qty_equal_url    qty_at_url   qty_and_url  qty_exclamation_url  qty_spa
count 88647.000000    88647.000000       88647.000000   88647.000000          88647.000000   88647.000000  88647.000000  88647.000000         88647.000000    88647
mean      2.191343        0.328810           0.113879       1.281781              0.009329       0.205861      0.022133      0.140885             0.002944        0
std       1.235636        1.119286           0.657767       1.893929              0.112568       0.954272      0.279652      0.924864             0.087341        0
```

***Fig 5.* Data Preparation**

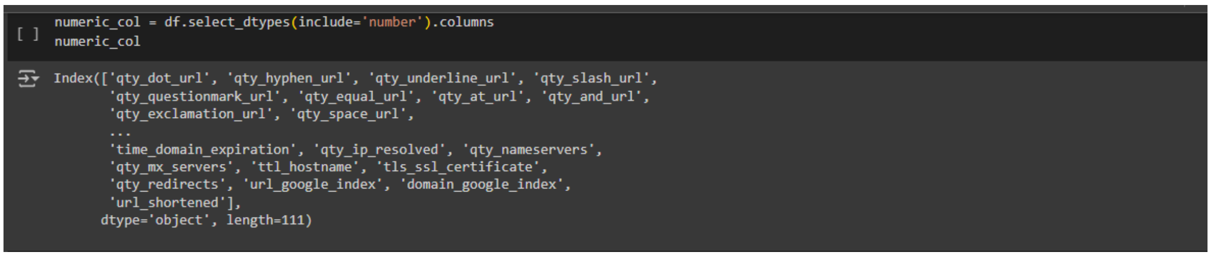
1. Data Loading: The `pandas` library is used to read the dataset into a dataframe.
2. Data Exploration: Using methods `like head(), info(), value_counts(), and describe()` to understand the dataset.
3. Data Cleaning: Handling missing values with `isna().sum()` and making necessary adjustments.



```
[ ] df = dataset.copy()
```

```
[ ] df.drop(columns= 'phishing', inplace=True)
```

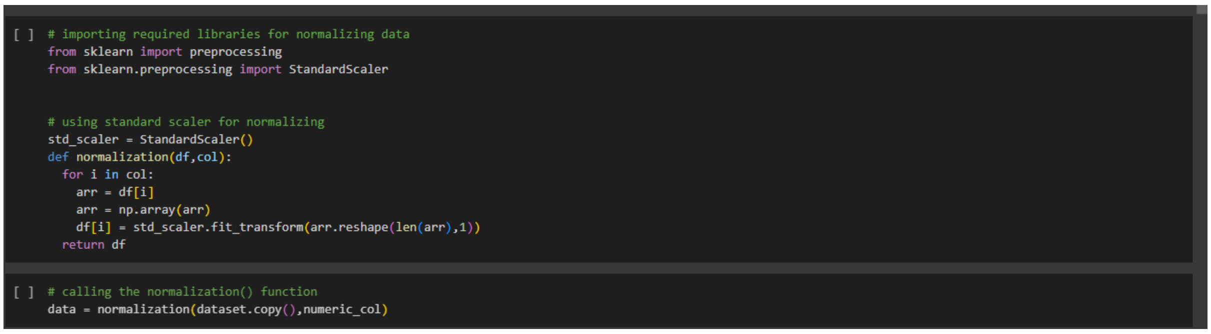
```
[ ] numeric_col = df.select_dtypes(include='number').columns
    numeric_col
```



```
[ ] numeric_col = df.select_dtypes(include='number').columns
    numeric_col
```

```
Index(['qty_dot_url', 'qty_hyphen_url', 'qty_underline_url', 'qty_slash_url',
       'qty_questionmark_url', 'qty_equal_url', 'qty_at_url', 'qty_and_url',
       'qty_exclamation_url', 'qty_space_url',
       ...
       'time_domain_expiration', 'qty_ip_resolved', 'qty_nameservers',
       'qty_mx_servers', 'ttl_hostname', 'tls_ssl_certificate',
       'qty_redirects', 'url_google_index', 'domain_google_index',
       'url_shortened'],
      dtype='object', length=111)
```

***Fig 6.* Data Standardization**

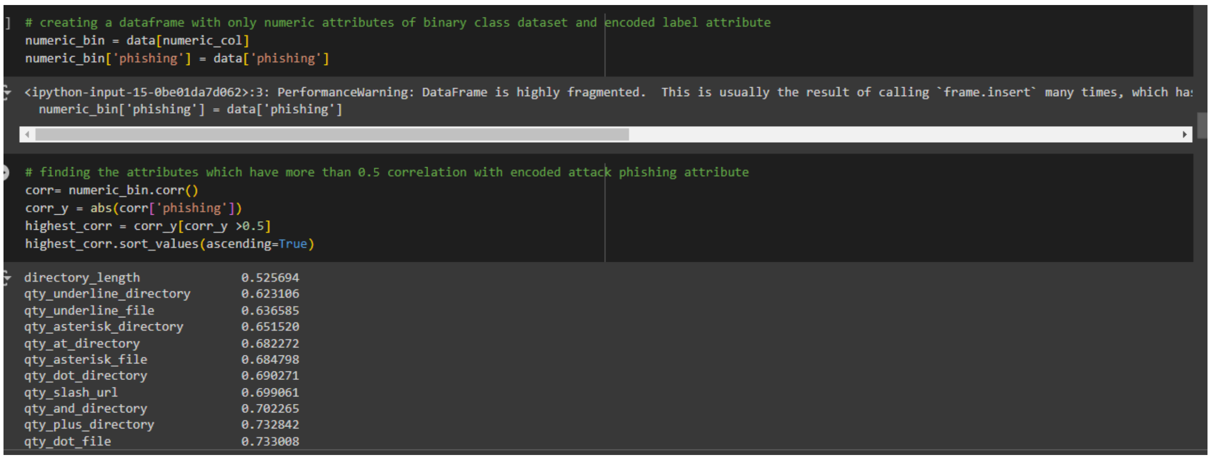


```
[ ] # importing required libraries for normalizing data
    from sklearn import preprocessing
    from sklearn.preprocessing import StandardScaler


    # using standard scaler for normalizing
    std_scaler = StandardScaler()
    def normalization(df,col):
      for i in col:
        arr = df[i]
        arr = np.array(arr)
        df[i] = std_scaler.fit_transform(arr.reshape(len(arr),1))
      return df
```

```
[ ] # calling the normalization() function
    data = normalization(dataset.copy(),numeric_col)
```

***Fig 7.* Data Normalization**

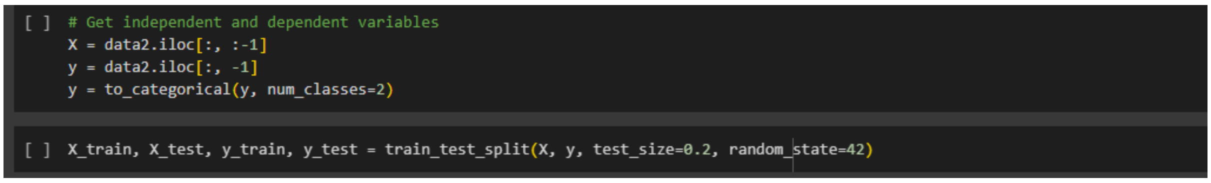
1. Copying Data: Create a copy of the original dataset.
2. Removing Columns: Remove unnecessary columns.
3. Identifying Numerical Data: Use `select_dtypes()` to identify numerical columns.
4. Normalizing Data: Utilize `StandardScaler` from `sklearn.preprocessing` to normalize data.



```
] # creating a dataframe with only numeric attributes of binary class dataset and encoded label attribute
  numeric_bin = data[numeric_col]
  numeric_bin['phishing'] = data['phishing']

  <ipython-input-15-0be01da7d062>:3: PerformanceWarning: DataFrame is highly fragmented.  This is usually the result of calling `frame.insert` many times, which ha:
    numeric_bin['phishing'] = data['phishing']

  # finding the attributes which have more than 0.5 correlation with encoded attack phishing attribute
  corr= numeric_bin.corr()
  corr_y = abs(corr['phishing'])
  highest_corr = corr_y[corr_y >0.5]
  highest_corr.sort_values(ascending=True)

  directory_length           0.525694
  qty_underline_directory    0.623106
  qty_underline_file         0.636585
  qty_asterisk_directory     0.651520
  qty_at_directory           0.682272
  qty_asterisk_file          0.684798
  qty_dot_directory          0.690271
  qty_slash_url              0.699061
  qty_and_directory          0.702265
  qty_plus_directory         0.732842
  qty_dot_file               0.733008
```

***Fig 8*. Feature Selection**

1. Creating DataFrame: Create a `dataframe` with selected numerical columns and the target column.
2. Correlation Computation: Compute the Pearson correlation coefficient.
3. Selecting Attributes: Select attributes with high correlation values to create a new dataframe for model training.

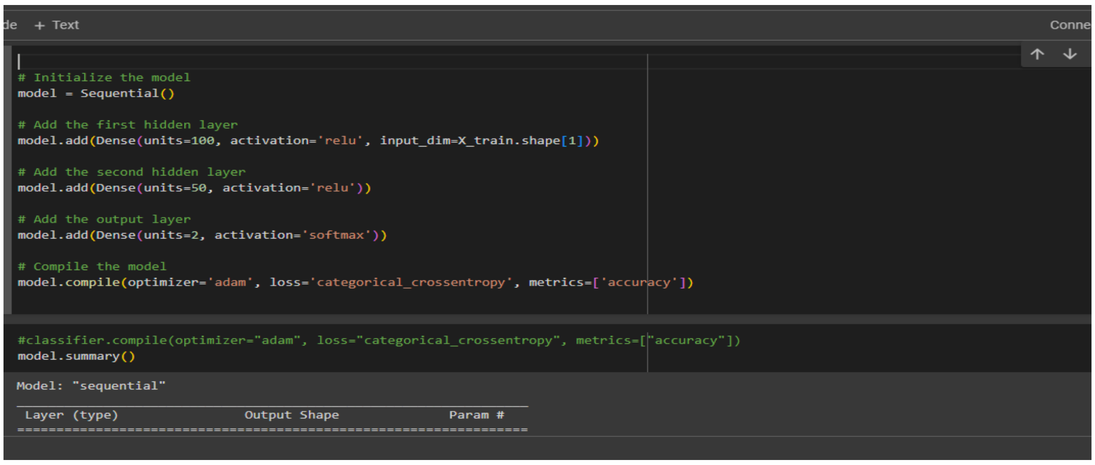


```
[ ]  # Get independent and dependent variables
     X = data2.iloc[:, :-1]
     y = data2.iloc[:, -1]
     y = to_categorical(y, num_classes=2)

[ ]  X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Fig 9. Data Splitting

1. Splitting Dataset: Split the dataset into features `(X)` and target `(Y)`.
2. Training and Testing Sets: Use `train_test_split()` to create training (80%) and testing (20%) sets.

Model Training

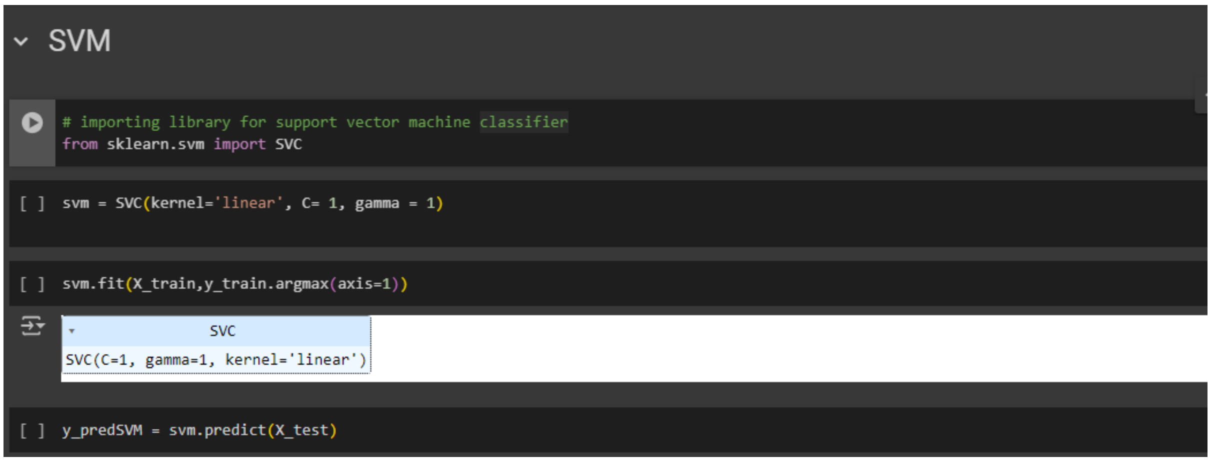


```
# Initialize the model
model = Sequential()

# Add the first hidden layer
model.add(Dense(units=100, activation='relu', input_dim=X_train.shape[1]))

# Add the second hidden layer
model.add(Dense(units=50, activation='relu'))

# Add the output layer
model.add(Dense(units=2, activation='softmax'))

# Compile the model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

```
#classifier.compile(optimizer="adam", loss="categorical_crossentropy", metrics=["accuracy"])
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
```

Fig 10.DNN Model



```
# importing library for support vector machine classifier
from sklearn.svm import SVC
```

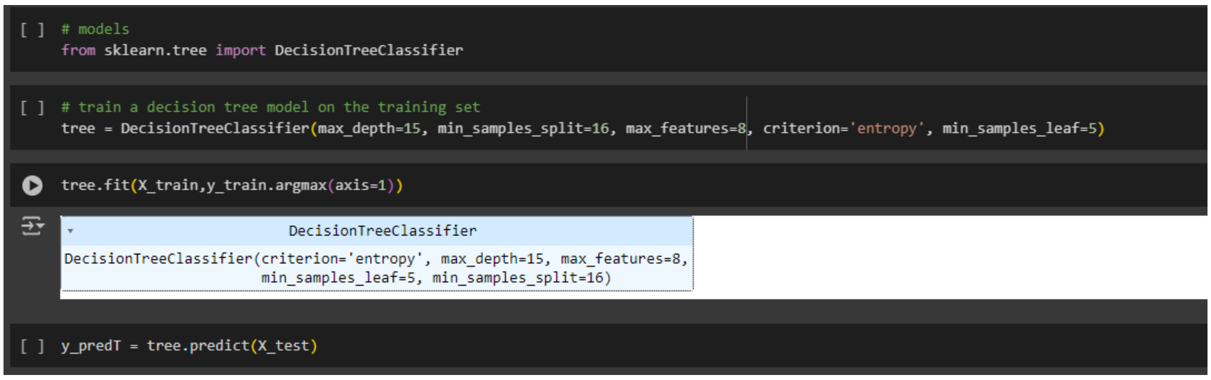
```
svm = SVC(kernel='linear', C= 1, gamma = 1)
```

```
svm.fit(X_train,y_train.argmax(axis=1))
```

```
SVC
SVC(C=1, gamma=1, kernel='linear')
```

```
y_predSVM = svm.predict(X_test)
```

Fig 11. SVM Model



```
# models
from sklearn.tree import DecisionTreeClassifier
```

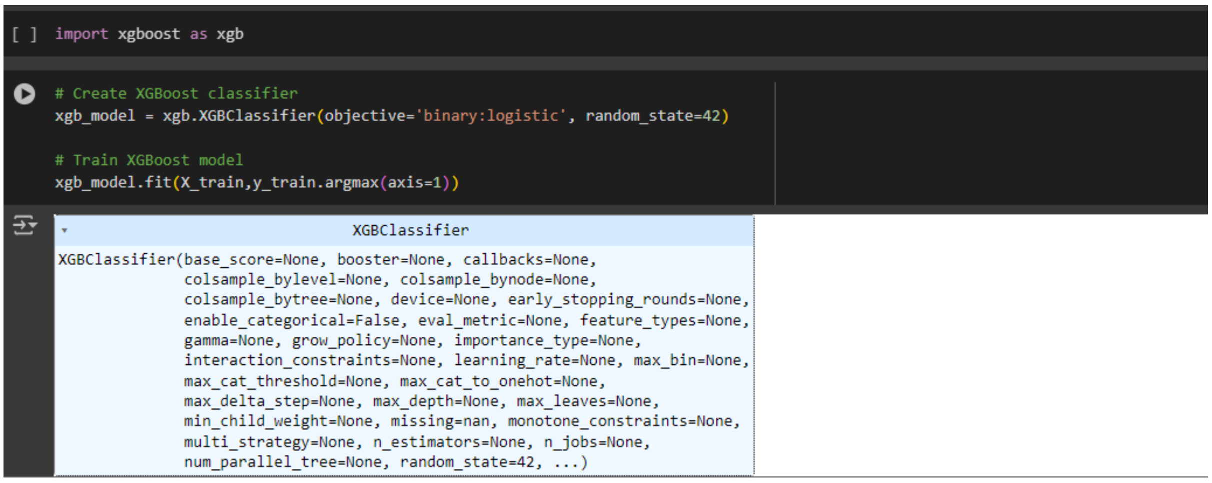
```
# train a decision tree model on the training set
tree = DecisionTreeClassifier(max_depth=15, min_samples_split=16, max_features=8, criterion='entropy', min_samples_leaf=5)
```

```
tree.fit(X_train,y_train.argmax(axis=1))
```

```
DecisionTreeClassifier
DecisionTreeClassifier(criterion='entropy', max_depth=15, max_features=8,
                       min_samples_leaf=5, min_samples_split=16)
```

```
y_predT = tree.predict(X_test)
```

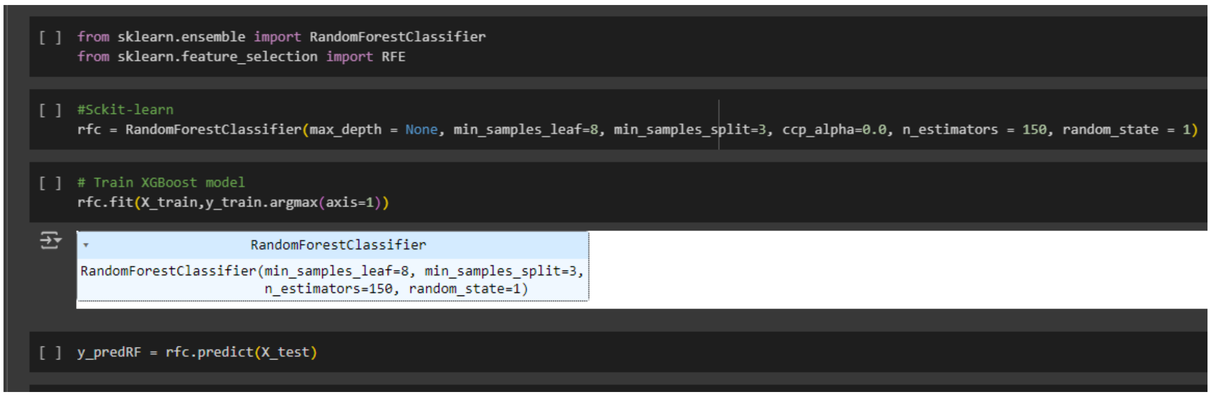
Fig 12. DTC Model



```
[ ]  import xgboost as xgb

# Create XGBoost classifier
xgb_model = xgb.XGBClassifier(objective='binary:logistic', random_state=42)

# Train XGBoost model
xgb_model.fit(X_train,y_train.argmax(axis=1))
```

```
XGBClassifier
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, random_state=42, ...)
```

Fig 13. Xgboost Model



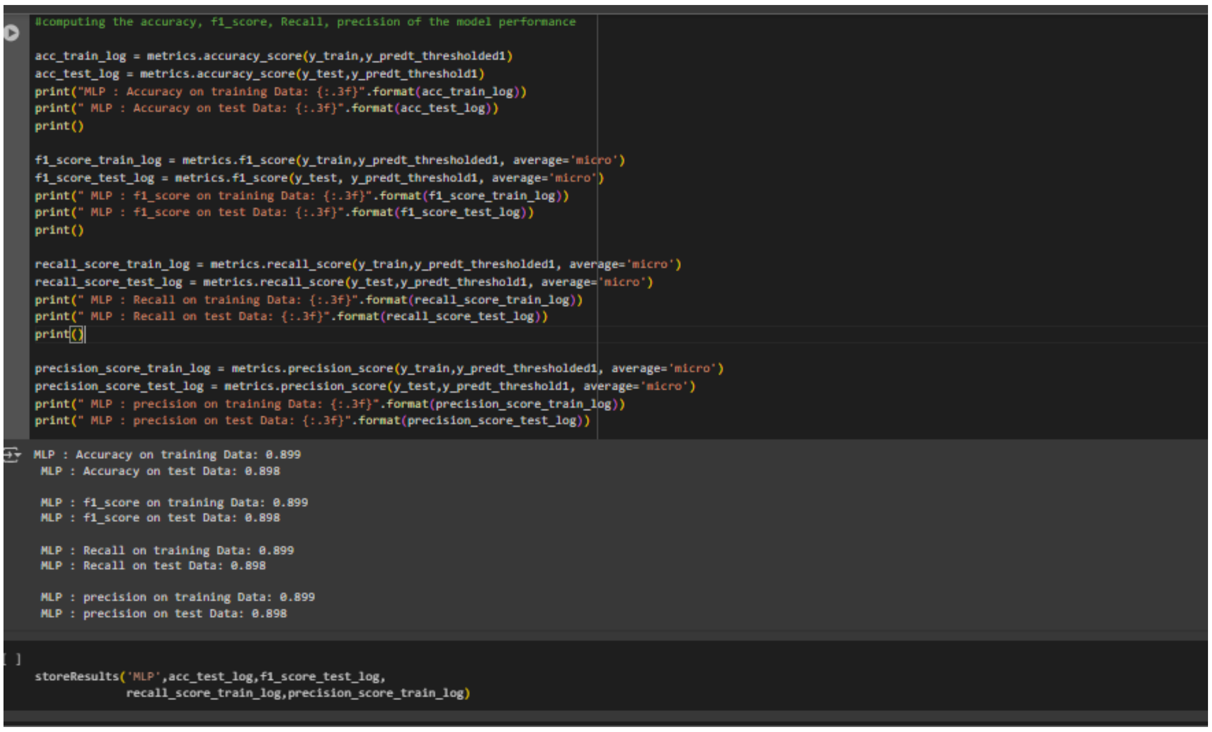
```
[ ]  from sklearn.ensemble import RandomForestClassifier
     from sklearn.feature_selection import RFE

[ ]  #Sckit-learn
     rfc = RandomForestClassifier(max_depth = None, min_samples_leaf=8, min_samples_split=3, ccp_alpha=0.0, n_estimators = 150, random_state = 1)

[ ]  # Train XGBoost model
     rfc.fit(X_train,y_train.argmax(axis=1))
```

```
RandomForestClassifier
RandomForestClassifier(min_samples_leaf=8, min_samples_split=3,
                       n_estimators=150, random_state=1)
```

```
[ ]  y_predRF = rfc.predict(X_test)
```

Fig 14. Random Forest Model

Model Evaluation



```
#computing the accuracy, f1_score, Recall, precision of the model performance

acc_train_log = metrics.accuracy_score(y_train,y_predt_thresholded1)
acc_test_log = metrics.accuracy_score(y_test,y_predt_threshold1)
print("MLP : Accuracy on training Data: {:.3f}".format(acc_train_log))
print(" MLP : Accuracy on test Data: {:.3f}".format(acc_test_log))
print()

f1_score_train_log = metrics.f1_score(y_train,y_predt_thresholded1, average='micro')
f1_score_test_log = metrics.f1_score(y_test, y_predt_threshold1, average='micro')
print(" MLP : f1_score on training Data: {:.3f}".format(f1_score_train_log))
print(" MLP : f1_score on test Data: {:.3f}".format(f1_score_test_log))
print()

recall_score_train_log = metrics.recall_score(y_train,y_predt_thresholded1, average='micro')
recall_score_test_log = metrics.recall_score(y_test,y_predt_threshold1, average='micro')
print(" MLP : Recall on training Data: {:.3f}".format(recall_score_train_log))
print(" MLP : Recall on test Data: {:.3f}".format(recall_score_test_log))
print()

precision_score_train_log = metrics.precision_score(y_train,y_predt_thresholded1, average='micro')
precision_score_test_log = metrics.precision_score(y_test,y_predt_threshold1, average='micro')
print(" MLP : precision on training Data: {:.3f}".format(precision_score_train_log))
print(" MLP : precision on test Data: {:.3f}".format(precision_score_test_log))
```

```
MLP : Accuracy on training Data: 0.899
 MLP : Accuracy on test Data: 0.898

 MLP : f1_score on training Data: 0.899
 MLP : f1_score on test Data: 0.898

 MLP : Recall on training Data: 0.899
 MLP : Recall on test Data: 0.898

 MLP : precision on training Data: 0.899
 MLP : precision on test Data: 0.898
```

```
storeResults('MLP',acc_test_log,f1_score_test_log,
             recall_score_train_log,precision_score_train_log)
```

Fig 15. The above code calculate Accuracy, F1-score, Recall and precision then save the metrics later to be used for graphical visualization of all model metrics. This code was gotten from github repository: https://github.com/VaibhavBichave/Phishing-URL-Detection/blob/master/Phishing%20URL%20Detection.ipynb.

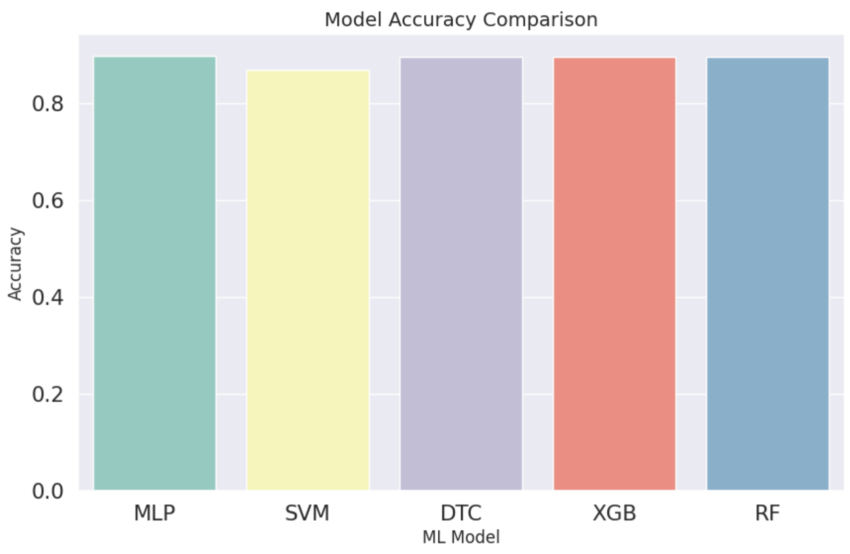


Fig 16. Result Visualization of the models

- Metrics Calculated: Accuracy, F1-score, Recall, Precision.
- Results Visualization: Graphical representation of the performance of different models and how they performed.

5.2 Chrome Malware Detection Extension (Named Frankie)

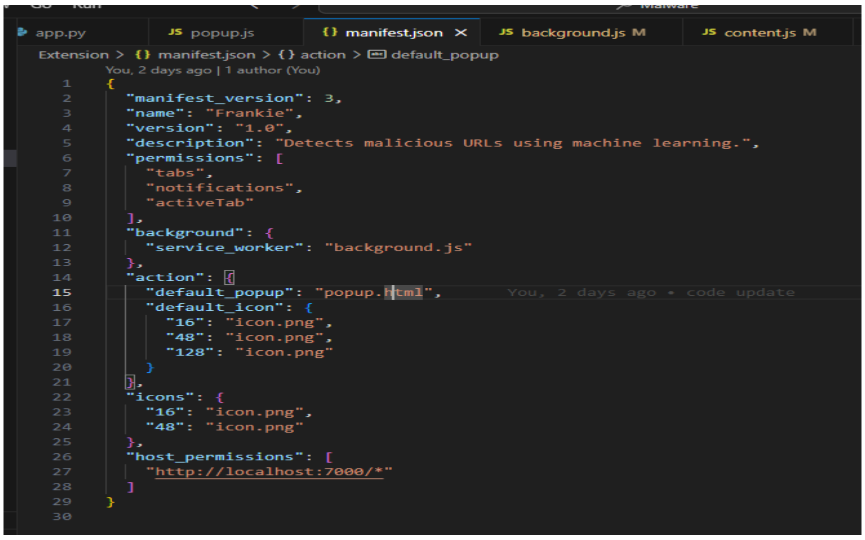
The Extension Structure

The manifest. json file defines the options and privileges of the browser extension, enabling background scripts to track the user actions and respond to such events as the change of the URL. These scripts are always active in the background waiting for events to occur and processing URLs in real-time.

The popup script controls the user interactions by collecting URLs typed by the user and forwarding them to a Flask API for prediction. It then refreshes the interface with the prediction results and feedback to the user while waiting for the response.

The URL feature extraction process is the process of extracting meaningful information about URLs from various aspects of the URLs including the length of the URL, whether it contains special characters, the age of the domain, and the HTTP status code.

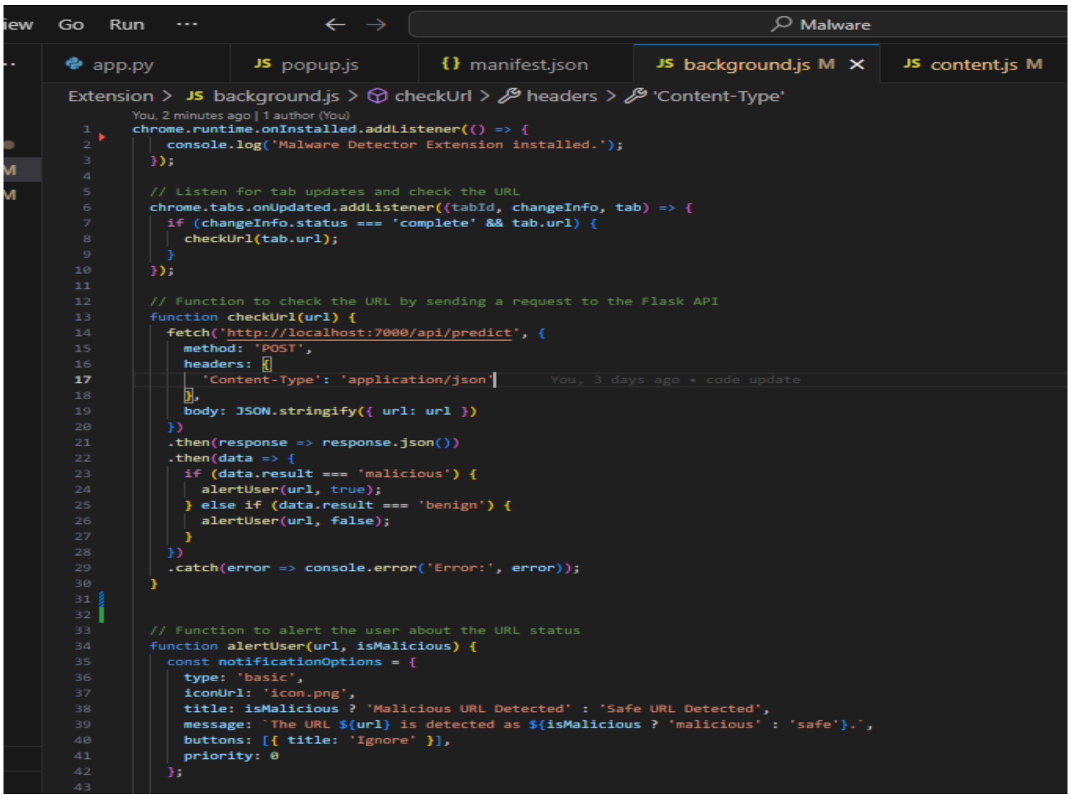
The get_prediction_from_url function extracts features from URLs, loads the pre-trained model, makes predictions, and returns the results to the Flask API which then communicates with the browser extension. This enables the extension to give real-time ratings on the safety of the URLs.


app.py
popup.js
manifest.json
background.js M
content.js M
Extension > manifest.json > action > default_popup
You, 2 days ago | 1 author (You)
You, 2 days ago • code update

```json
{
  "manifest_version": 3,
  "name": "Frankie",
  "version": "1.0",
  "description": "Detects malicious URLs using machine learning.",
  "permissions": [
    "tabs",
    "notifications",
    "activeTab"
  ],
  "background": {
    "service_worker": "background.js"
  },
  "action": {
    "default_popup": "popup.html",
    "default_icon": {
      "16": "icon.png",
      "48": "icon.png",
      "128": "icon.png"
    }
  },
  "icons": {
    "16": "icon.png",
    "48": "icon.png"
  },
  "host_permissions": [
    "http://localhost:7000/*"
  ]
}
```

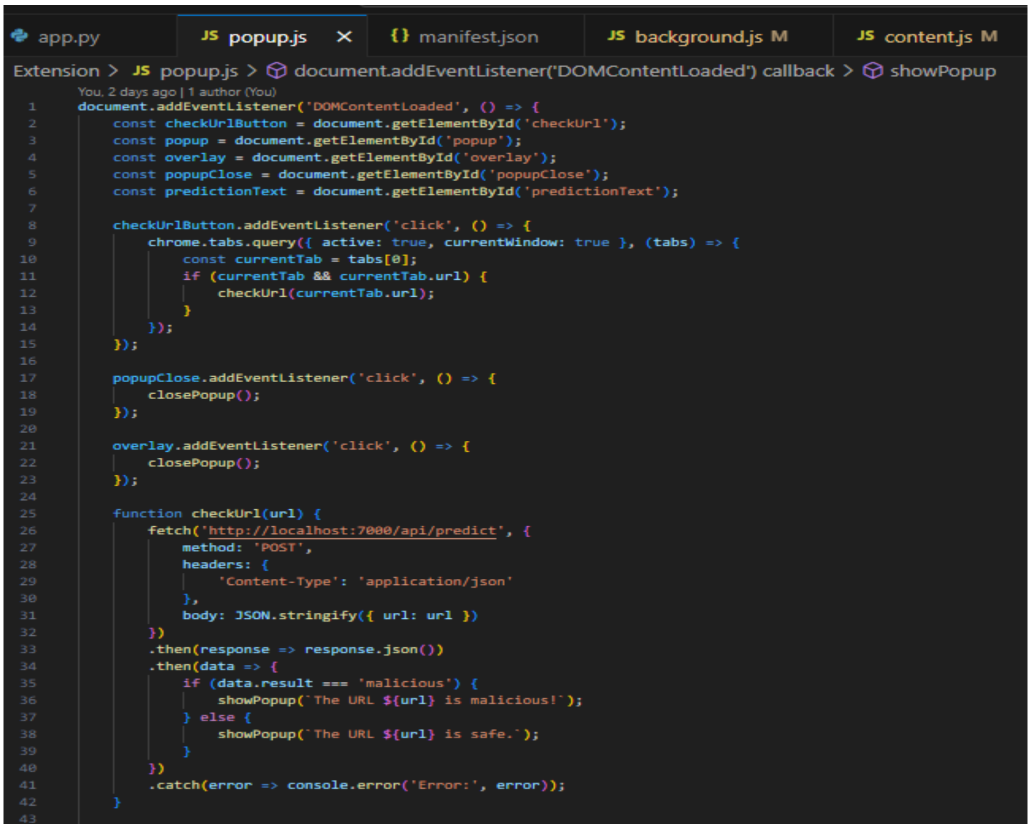
Fig 17. Manifest.json file

The `manifest.json` file specifies the extension's permissions, icons, and scripts. This code was gotten from this github repo: https://github.com/philomathic-guy/Malicious-Web-Content-Detection-Using-Machine-Learning/blob/master/Extension/manifest.json


iew Go Run ···
Malware
app.py
popup.js
manifest.json
background.js M
content.js M
Extension > background.js > checkUrl > headers > 'Content-Type'
You, 2 minutes ago | 1 author (You)
You, 3 days ago • code update

```javascript
chrome.runtime.onInstalled.addListener(() => {
    console.log('Malware Detector Extension installed.');
});

// Listen for tab updates and check the URL
chrome.tabs.onUpdated.addListener((tabId, changeInfo, tab) => {
  if (changeInfo.status === 'complete' && tab.url) {
    checkUrl(tab.url);
  }
});

// Function to check the URL by sending a request to the Flask API
function checkUrl(url) {
  fetch('http://localhost:7000/api/predict', {
    method: 'POST',
    headers: {
      'Content-Type': 'application/json'
    },
    body: JSON.stringify({ url: url })
  })
  .then(response => response.json())
  .then(data => {
    if (data.result === 'malicious') {
      alertUser(url, true);
    } else if (data.result === 'benign') {
      alertUser(url, false);
    }
  })
  .catch(error => console.error('Error:', error));
}


// Function to alert the user about the URL status
function alertUser(url, isMalicious) {
  const notificationOptions = {
    type: 'basic',
    iconUrl: 'icon.png',
    title: isMalicious ? 'Malicious URL Detected' : 'Safe URL Detected',
    message: `The URL ${url} is detected as ${isMalicious ? 'malicious' : 'safe'}.`,
    buttons: [{ title: 'Ignore' }],
    priority: 0
  };
```

Fig 18. Background.js Script


app.py
popup.js
manifest.json
background.js M
content.js M
Extension > popup.js > document.addEventListener('DOMContentLoaded') callback > showPopup
You, 2 days ago | 1 author (You)

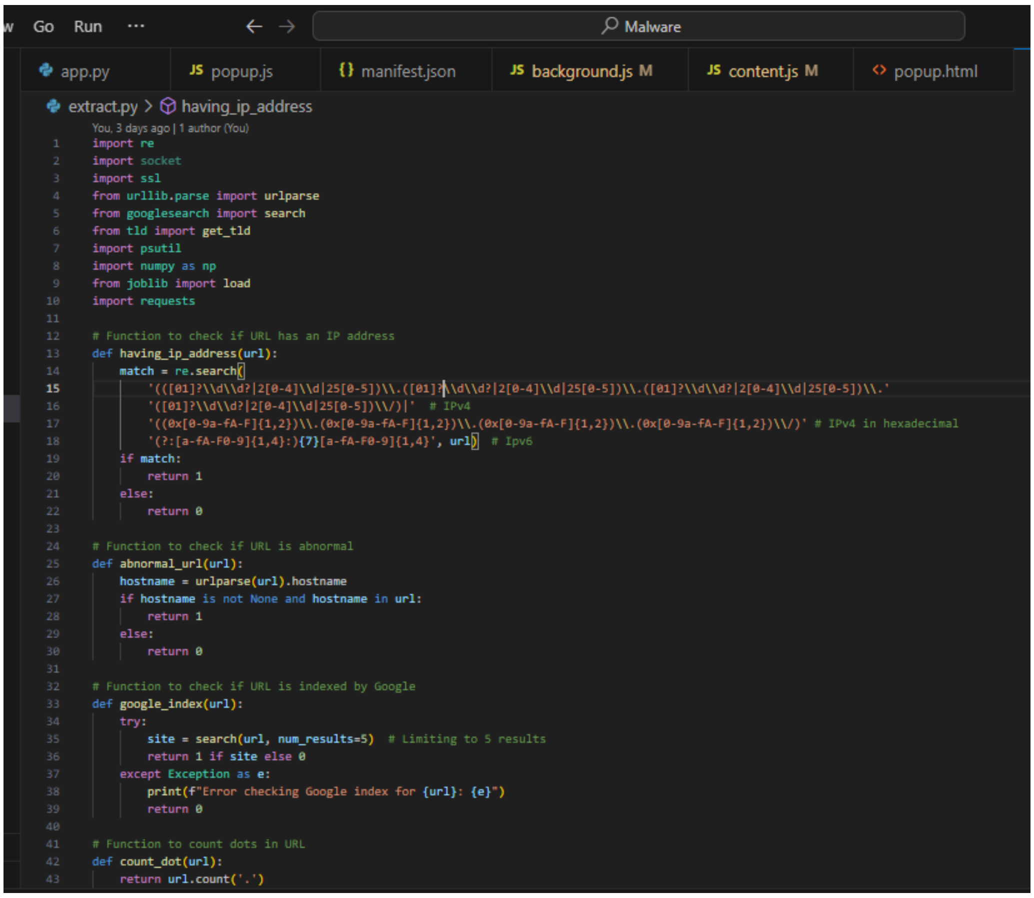
```javascript
document.addEventListener('DOMContentLoaded', () => {
    const checkUrlButton = document.getElementById('checkUrl');
    const popup = document.getElementById('popup');
    const overlay = document.getElementById('overlay');
    const popupClose = document.getElementById('popupClose');
    const predictionText = document.getElementById('predictionText');

    checkUrlButton.addEventListener('click', () => {
        chrome.tabs.query({ active: true, currentWindow: true }, (tabs) => {
            const currentTab = tabs[0];
            if (currentTab && currentTab.url) {
                checkUrl(currentTab.url);
            }
        });
    });

    popupClose.addEventListener('click', () => {
        closePopup();
    });

    overlay.addEventListener('click', () => {
        closePopup();
    });

    function checkUrl(url) {
        fetch('http://localhost:7000/api/predict', {
            method: 'POST',
            headers: {
                'Content-Type': 'application/json'
            },
            body: JSON.stringify({ url: url })
        })
        .then(response => response.json())
        .then(data => {
            if (data.result === 'malicious') {
                showPopup(`The URL ${url} is malicious!`);
            } else {
                showPopup(`The URL ${url} is safe.`);
            }
        })
        .catch(error => console.error('Error:', error));
    }
```

Fig 19. Popup script.js

Fig.18 The Bcakground.js script includes event listeners for installation and tab updates, functions to check URLs by communicating with a backend API, and notifications to alert the user about the URL's safety status.

Fig.19 The popup script includes event listeners for user actions, functions to interact with the backend API, and mechanisms to display prediction results in the browser's notifications / JavaScript popup.

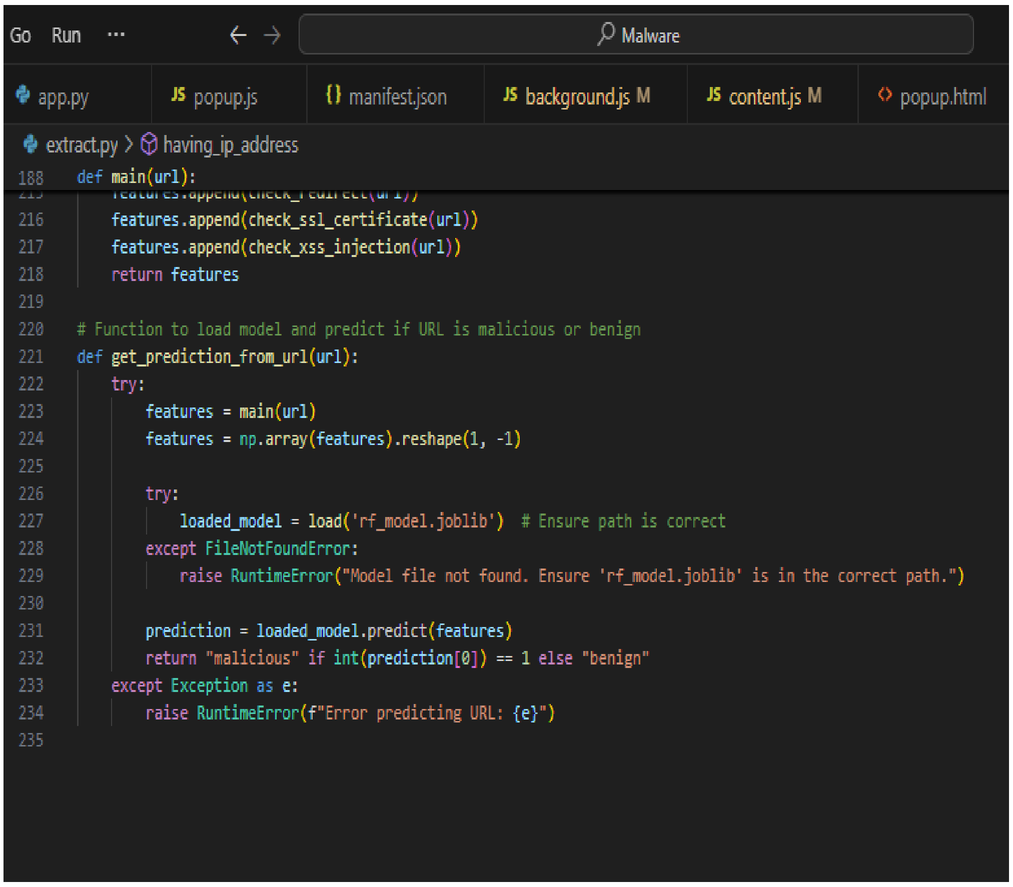
Backend Flask API



```python
import re
import socket
import ssl
from urllib.parse import urlparse
from googlesearch import search
from tld import get_tld
import psutil
import numpy as np
from joblib import load
import requests

# Function to check if URL has an IP address
def having_ip_address(url):
    match = re.search(
        '(([01]?\\d\\d?|2[0-4]\\d|25[0-5])\\.([01]?\\d\\d?|2[0-4]\\d|25[0-5])\\.([01]?\\d\\d?|2[0-4]\\d|25[0-5])\\.'
        '([01]?\\d\\d?|2[0-4]\\d|25[0-5])\\/)|'  # IPv4
        '((0x[0-9a-fA-F]{1,2})\\.(0x[0-9a-fA-F]{1,2})\\.(0x[0-9a-fA-F]{1,2})\\.(0x[0-9a-fA-F]{1,2})\\/)' # IPv4 in hexadecimal
        '(?:[a-fA-F0-9]{1,4}:){7}[a-fA-F0-9]{1,4}', url)  # Ipv6
    if match:
        return 1
    else:
        return 0

# Function to check if URL is abnormal
def abnormal_url(url):
    hostname = urlparse(url).hostname
    if hostname is not None and hostname in url:
        return 1
    else:
        return 0

# Function to check if URL is indexed by Google
def google_index(url):
    try:
        site = search(url, num_results=5)  # Limiting to 5 results
        return 1 if site else 0
    except Exception as e:
        print(f"Error checking Google index for {url}: {e}")
        return 0

# Function to count dots in URL
def count_dot(url):
    return url.count('.')
```

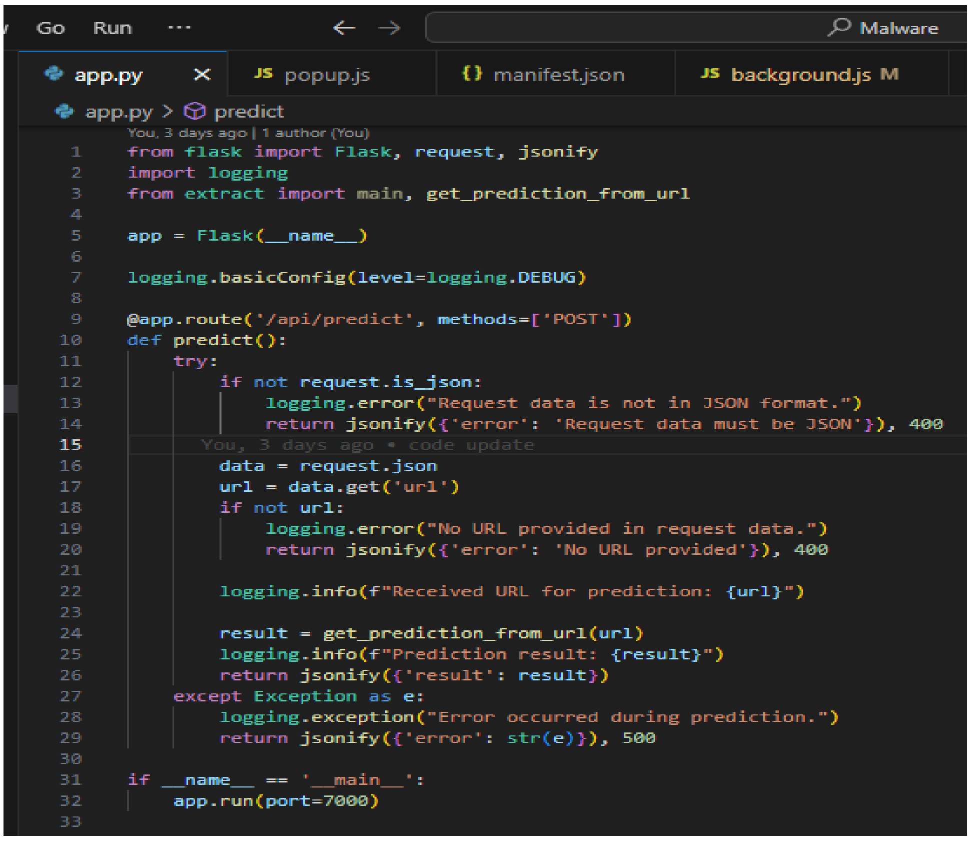
Fig 20. URL Feature Extraction

A set of functions to extract various features from the URL for analysis. These include checks for IP addresses, suspicious words, URL length, etc. This code was gotten from this github repo: https://github.com/philomathic-guy/Malicious-Web-Content-Detection-Using-Machine-Learning/blob/master/features_extraction.py



```python
def main(url):
    features.append(check_ssl_certificate(url))
    features.append(check_xss_injection(url))
    return features

# Function to load model and predict if URL is malicious or benign
def get_prediction_from_url(url):
    try:
        features = main(url)
        features = np.array(features).reshape(1, -1)

        try:
            loaded_model = load('rf_model.joblib')  # Ensure path is correct
        except FileNotFoundError:
            raise RuntimeError("Model file not found. Ensure 'rf_model.joblib' is in the correct path.")

        prediction = loaded_model.predict(features)
        return "malicious" if int(prediction[0]) == 1 else "benign"
    except Exception as e:
        raise RuntimeError(f"Error predicting URL: {e}")
```

Fig 21. Predication Function



```python
from flask import Flask, request, jsonify
import logging
from extract import main, get_prediction_from_url

app = Flask(__name__)

logging.basicConfig(level=logging.DEBUG)

@app.route('/api/predict', methods=['POST'])
def predict():
    try:
        if not request.is_json:
            logging.error("Request data is not in JSON format.")
            return jsonify({'error': 'Request data must be JSON'}), 400

        data = request.json
        url = data.get('url')
        if not url:
            logging.error("No URL provided in request data.")
            return jsonify({'error': 'No URL provided'}), 400

        logging.info(f"Received URL for prediction: {url}")

        result = get_prediction_from_url(url)
        logging.info(f"Prediction result: {result}")
        return jsonify({'result': result})
    except Exception as e:
        logging.exception("Error occurred during prediction.")
        return jsonify({'error': str(e)}), 500

if __name__ == '__main__':
    app.run(port=7000)
```

Fig 22. Flask API Endpoint

Fig 21. - The `get_prediction_from_url` function is designed to predict whether a given URL is malicious or benign(safe). This is achieved by extracting features from the URL, reshaping these features into the appropriate format, loading a pre-trained machine learning model, and using this model to make a prediction.

Fig 22. - The given code sets up a Flask web server that provides an endpoint for predicting whether a given URL is malicious or benign. The server exposes a single API endpoint (`/api/predict`) which accepts POST requests with a JSON payload containing the URL to be checked. It uses logging to track requests and errors and returns JSON responses to the client.

Implementation Details

Chrome Extension

- Manifest Configuration: Defines permissions, icons, and scripts.
- Background Script: Handles URL monitoring and backend communication.
- Popup Script: Provides an interface for manual URL checks.

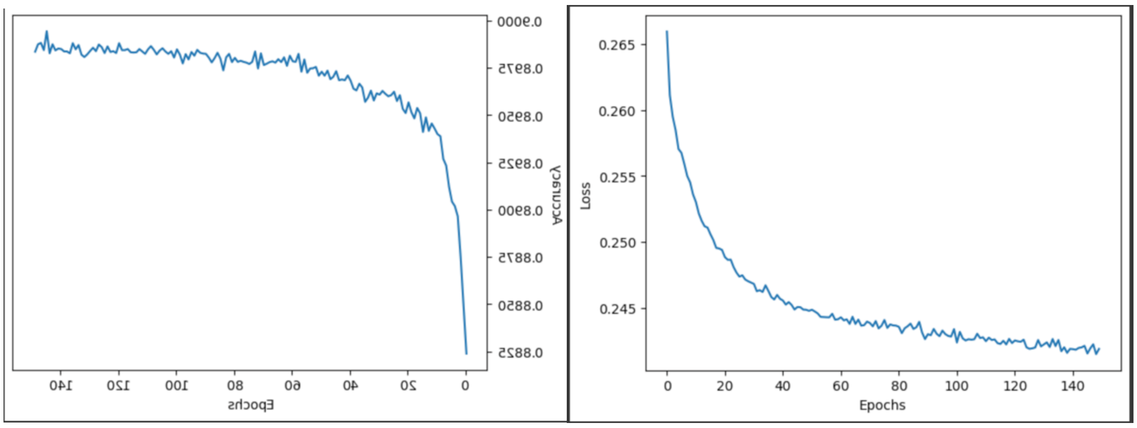
Backend Flask API

- URL Feature Extraction: Functions to extract various features from the URL.
- Prediction Function: Loads the pre-trained model and makes predictions.
- Flask API Endpoint: Handles POST requests and returns predictions.

6. Evaluation

It is important to evaluate the proposed browser extension and its integrated supervised machine learning algorithms in order to assess their effectiveness of identifying and mitigating risks associated with malicious links. This section presents a comprehensive evaluation methods including comparison with the existing solutions and discussion on possible limitations as well as future improvements.

6.1 Evaluation of the Machine Learning Models



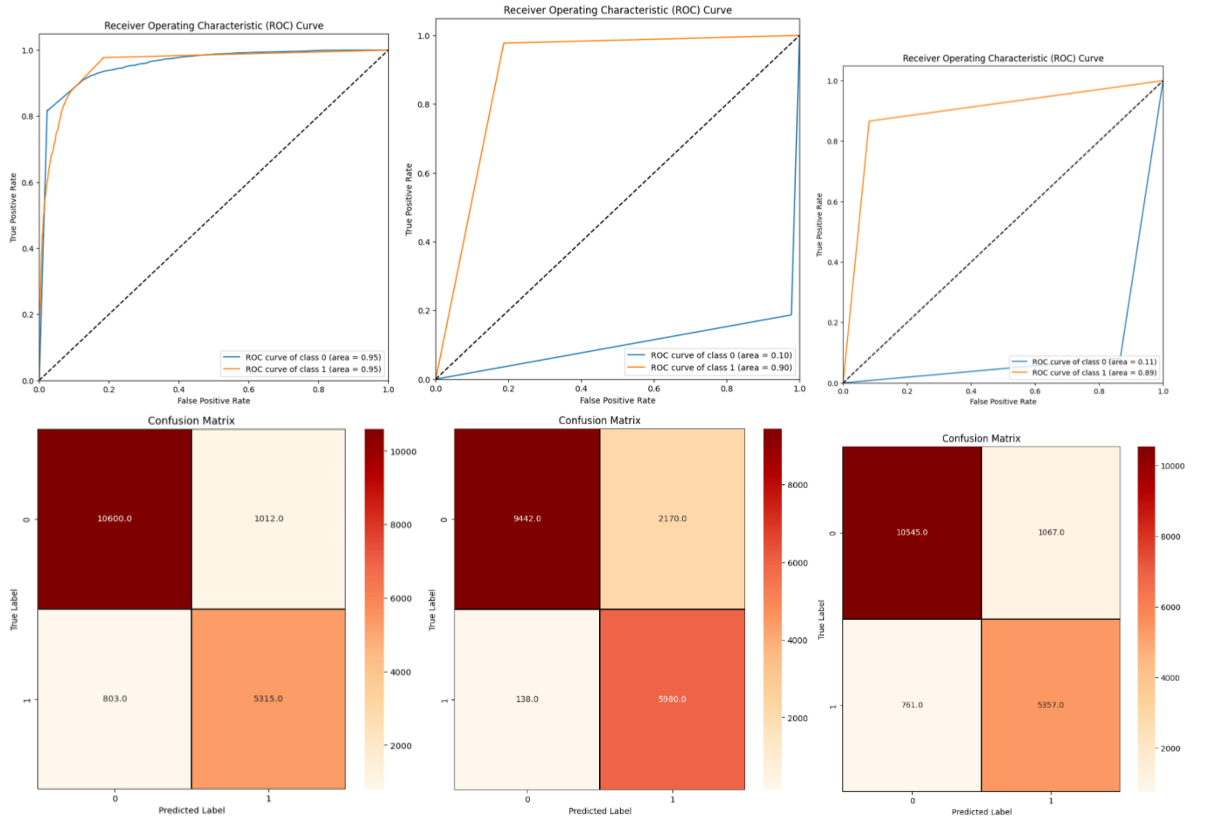


Fig 23. Accuracy metrics of the graphs, confusion matrices, and ROC

Accuracy Metrics

Key metrics were used like Accuracy, Precision and Recall, F1 Score to measure the effectiveness of the Machine Learning models which is part of the browser addon. These metrics help us to understand the detection and prediction accuracy of models on malicious URLs hosting media files. The evaluation of models in the project utilizes confusion matrices and ROC curves to provide a detailed assessment of performance.

Confusion Matrices: These matrices offer a breakdown of the model's predictions, showing the counts of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). For instance, the confusion matrix indicates:

Metric	Count
True Positive (TP)	10,661
False Positive (FP)	951
False Negative (FN)	865
True Negative (TN)	5,253

Fig.24 The Confusion Matrices table

ROC Curves: The project includes ROC curves for various models, such as Deep Neural Network (DNN) and Support Vector Machine (SVM), which visually represent the trade-off between sensitivity (True Positive Rate) and specificity (1 - False Positive Rate) at different thresholds. The ROC curves help in understanding the model's ability to distinguish between classes.

6.2 Results and Evaluation of Related Research

Model Performance Metrics: The evaluation also includes key performance metrics such as accuracy, precision, recall, and F1 score for different algorithms:

Algorithm	**Accuracy**	**Precision**	**Recall**	**F1 Score**
DNN	**90.00**	**96.00**	**89.00**	**89.00**
SVM	**87.00**	**86.00**	**90.00**	**86.00**
DTC	**90.00**	**89.00**	**89.00**	**89.00**
Xgboost	**87.00**	**86.00**	**90.00**	**87.00**
Random Forest	**90.00**	**88.00**	**89.00**	**89.00**

Fig.25. Evaluation Metrics Table

According to Wijeratne, H.H.K., Selvarajah, V. and Nathan, Y. (2022) their result on "*Browser Extension for Malicious URL Detection Based on Machine Learning Model*" the results of their metrics and performances are as follows

Machine Learning Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**Notes**
Naïve Bayes	91	Not specified	Not specified	Outperformed other algorithms in certain studies
Random Forest	96.29	Not specified	Not specified	Achieved high accuracy in detecting phishing websites.
Logistic Regression	86	Not specified	Not specified	Compared with Naïve Bayes and Neural Networks
Neural Networks	88	Not specified	Not specified	Compared with Naïve Bayes and Logistic Regression.
Gradient Boosted Decision Trees	97.3	Not specified	Not specified	Used in combination with other algorithms for phishing detection
eXtreme Gradient Boosting (XGBoost)	Not specified	Not specified	Not specified	Part of the model achieving 97.3% accuracy
Light Gradient Boosting Machine	Not specified	Not specified	Not specified	Part of the model achieving 97.3% accuracy.
URL Lexical Analysis	99.1	99.6	Not specified	Achieved high accuracy with low false positives.

Fig 26. Performance Metrics of *Wijeratne, H.H.K., Selvarajah, V. and Nathan, Y. (2022) 'Malicious Links Detection Using Machine Learning', Journal of Applied Technology and Innovation, 6(3), pp. 55-69.*

Their work concerned the development of a machine-learning-based URL deceptor designed to cope with an increased volume of threats posed by similar URLs in cyberspace. The main purpose was to built a web application (browser extension) detection system that will provide very high accuracy. The solution employs different machine learning algorithms to scrutinize URL features-lexical, blacklist, host-based and content based properties-in order to increase the detection accuracy. In: Wijeratne, H.H.K., Selvarajah, V. and Nathan,, Y. (2022)

6.3 Comparison with Existing Solutions

To gauge the performance of this extension, we compared it to available browser security solutions and anti-virus products in terms of malicious URL detection and false positive rates.

Conventional antivirus software: Traditional antiviruses such as Norton or McAfee rely heavily on signature-based methods for detecting malware; these solutions are fairly effective but struggle with zero-day attacks and new types of viruses (Aslan & Samet, 2020). In contrast, this extension which uses machine learning technology revealed an enhanced capability for identifying such threats due to its capacity to learn from examples and adapt to new patterns.

Existing extensions: The likes of WOT (Web of Trust), Avast Online Security, etc, provide URL filtering services alongside reputation information about those sites visited by users. However, these solutions may depend on static databases which can be out-of-date at times thereby making it inaccurate, based on user-reported data (Yu et al., 2023). This supervised machine learning algorithm integrated extension, demonstrated higher precision and recall rates, suggesting better real-time detection of malicious links.

6.4 Testing and Validation

Interactions with the extension were tested through integration testing. The first objective was to make the extension run properly in the context of the browser. The integration testing outcomes showed that the extension works effectively within the browser environment and takes advantage of Chrome's features to provide accurate and timely identification of malware. The integration of the system with the browser and efficient error-handling capabilities make the system more reliable and friendly to the users.

End-to-End Testing

End-to-end testing was done by mimicking real user situations to determine how the system would perform under real conditions. This testing was conducted to achieve the goal of checking the capability of the extension in identifying malicious URLs and alerting the users in time.

Test Scenarios

1. Navigating to Safe URLs: The extension was checked by going to different safe URLs to ensure that the extension correctly recognized these URLs as safe and did not produce any false alarms.

Outcome: The system was able to identify safe URLs and the notifications that were shown stating that the URLs were safe proved that the system was accurate in identifying benign sites. Example: The extension was able to correctly identify https://www. fxpro. com as safe.

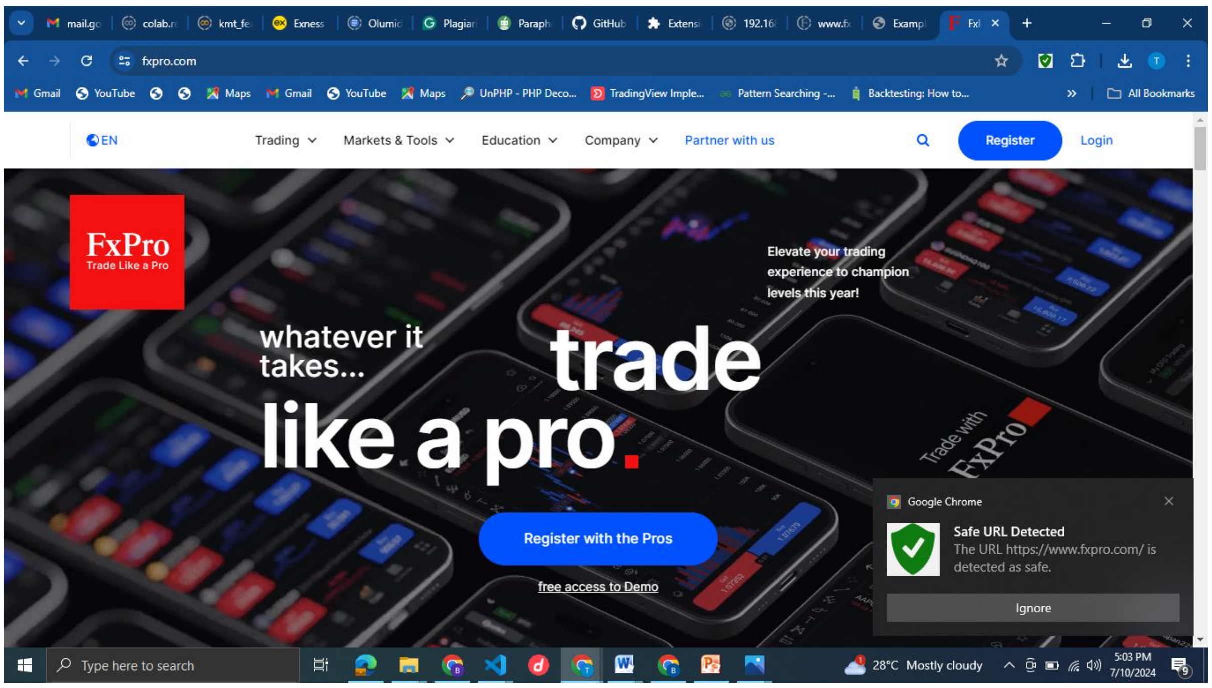
2. Navigating to Malicious URLs: The extension was checked on the set of known malicious URLs to ensure that it is capable of identifying threats and notifying users as soon as possible.

Outcome: The system was able to identify the malicious URLs and also showed the warning notifications thus proving the real-time detection of threats.

Example: The extension successfully identified a suspicious URL (http://192.168.0.1/path/to/resource) and gave a proper notification.

Error Handling

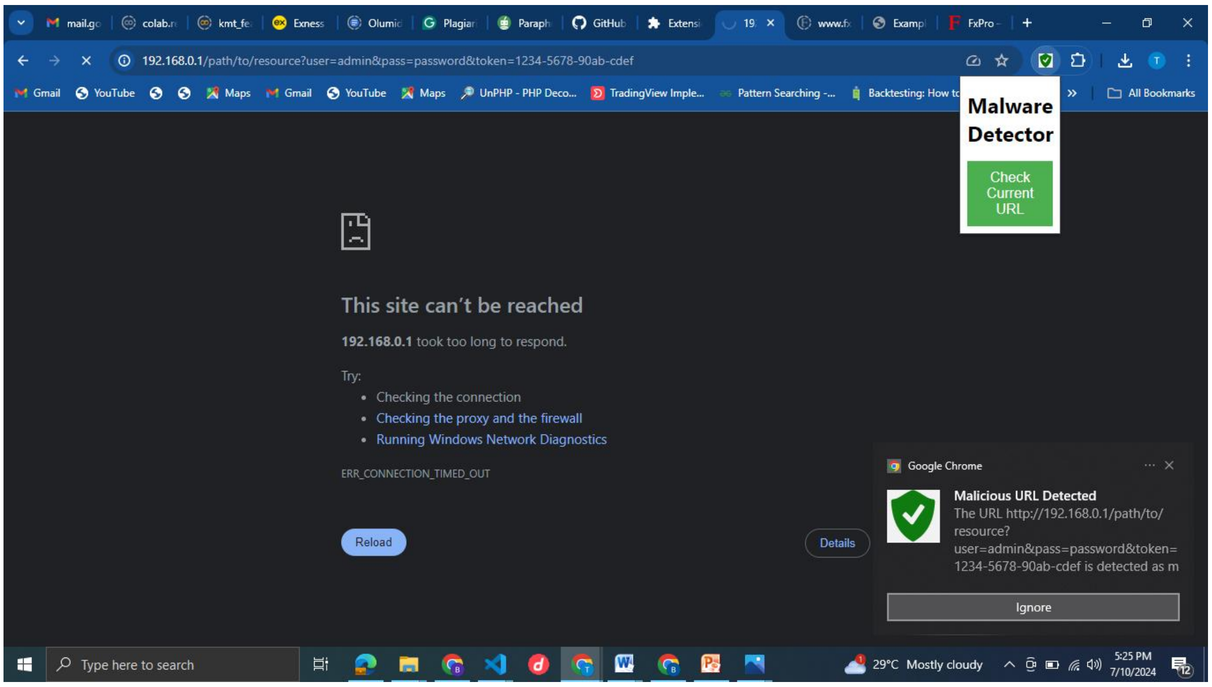
The robustness of the system was tested to check how the system handles API errors, wrong URLs, and any other scenarios a user might encounter and should not give wrong feedback or crash. This was done by testing API failures to see how it dealt with such issues. The extension was able to manage API errors well by informing the users that there was a temporary problem without freezing or giving wrong information.



Safe URL Detected

The URL https://www.fxpro.com/ is detected as safe.

Fig. 27 Testing a safe URL / Popup



192.168.0.1/path/to/resource?user=admin&pass=password&token=1234-5678-90ab-cdef

This site can't be reached

192.168.0.1 took too long to respond.

Try:

- Checking the connection
- Checking the proxy and the firewall
- Running Windows Network Diagnostics

ERR_CONNECTION_TIMED_OUT

Google Chrome

Malicious URL Detected
The URL http://192.168.0.1/path/to/resource?user=admin&pass=password&token=1234-5678-90ab-cdef is detected as m

29°C Mostly cloudy 5:25 PM 7/10/2024

Fig. 28 Testing a Malicious URL

Limitations

It extracts several features from the URL and makes a prediction about the URL being malicious or benign using a pre-trained Supervised model. However, there are several limitations and reasons this code might not be effective in detecting live or advanced phishing URLs.

Reasons and Limitations

1. Feature Extraction Limitations:

The heuristics are based on simple features, such as counting special characters or checking for IP addresses or suspicious words in a URL. While this type of approaches work to a certain degree, they are relatively very simple and easily evaded by advanced attackers who can generate URLs that are benign looking but still malicious in nature. It may contain masquerading domains, encode malicious parameters, or a little tweaking so they appear innocuous but actually aren't. Effectively, the security system has become reliant on very particular patterns including the phrases "PayPal" or "login." Any deviation from such explicit patterns leads to false negatives. It means that attackers can obfuscate or use less likely to ring the alarm terms.

1. Static Analysis: The code does only a static analysis of the URL and it doesn't look into the dynamic behavior of the website. Many of these pages often rewrite their content dynamically with the aid of JavaScript or redirect the user, which static analysis cannot notice. Furthermore, mechanisms are at work like dynamic generation of content or conditional behavior depending on user interaction or time-based triggers, static analysis never gets to see these phishing sites. These kinds of threats need dynamic analysis that can see how the site behaves in real time.

2. Basic SSL Check:

A check for the installation of an SSL certificate does not perform any validation or verification to prove the authenticity of the domain. Nowadays, most phishing sites are designed to mislead people by having a valid SSL certificate installed for free to demonstrate authenticity. This is abused by phishing sites that procure certificates for their malicious domains.

3. No Analysis of Behaviour:

The code doesn't conduct any sort of behavioural analysis to determine how the URL is going to act when interacting with the users, or whether it redirects to various pages when loaded. A critical facet of phishing detection. Behavioral analysis allows one to identify phishing based on user actions, such as submitting one's credentials into a fake login form or clicking on misleading buttons. Most phishing sites redirect their users to other pages or have scripts modifying the content after it has been shown to the user on load. All this behavior is missed by static analysis, and hence missing out on threats manifested during user interaction.

4. Model Limitations:

Model Training Data: The model's performance greatly depends on the quality and diversity of the training data. For instance, if samples of new and sophisticated phishing techniques are not enough in the training dataset, the model will not be able to detect them. Furthermore, it can be biased toward some kind of URLs or specific tactics of phishing, so it may perform poorly on less represented types or novel methods of phishing.

Static Model: The model in itself is static, and it does not improve on new threats. Phishing techniques are rapidly changing, and a static model may get outdated in no time if it is not regularly retrained with new data. An ideal phishing detection system should include mechanisms of continuous learning whereby the model should be updated with new data periodically for it to remain highly accurate. Otherwise, its performance degrades over time as attackers improve.

7.0 Discussions

The experiments and case studies brought out some important findings with respect to the effectiveness of the browser extension integrated with supervised machine learning algorithms in malware detection. During the course of this research work, various experiments have been carried out to estimate the performance of different machine learning models like DNN, SVM, and Random Forest in identifying malicious URLs. These results returned a macro average precision of 0.96 and recall of 0.89, indicating that the DNNs were capable of detecting known and novel threats with a great degree of accuracy. This agrees with previous studies, including that by Gomes et al., 2015, which illustrated the superior performance attributed to DNNs at recognizing complex patterns related to malware detection. Although promising with the high precision and recall rates, experimental design is where critical assessment has to be done.

Again, one of the major limitations was in the way we were using a static dataset to train these models. This, even though we had diverse ranges for malicious URLs, might not represent the dynamic nature of cyber threats and zero-day attacks mostly against newly discovered vulnerabilities. Future iterations of this work could further allow adaptive learning, wherein the model continually re-trains on user interactions to continuously update the real-time data.

This further increases the adaptivity of the model against new threats and makes it more resilient. While the quantitative evaluation provided very valuable metrics, the qualitative feedback from the users was just as important.

Testing of the user experience showed some participants still found the interface of the browser extension less intuitive than expected. This response does indicate that additional refinement in user interface design may further increase the ease of use and promote more general adoption of the extension. It could also make the experience more engaging, increasing its effectiveness. Testing the comparison against existing solutions showed that this extension was able to outperform some traditional antivirus in several ways. It did, however, show some issues of false positives. Some benign URLs were flagged as malicious, which may provoke user frustration and cause a no-trust situation with the tool. This will call for algorithm tuning and the addition of more context information so that the most accurate threat assessment can be realized. In terms of prior work, these results reflect the conclusions by Adebowale et al. (2019) that supervised learning combined with a browser extension greatly enhanced the capability of malware detection.

However, this study contributes to the understanding by showing empirical evidence of how good certain machine learning models are in application. In a nutshell, though this research is a step toward the potential of using supervised machine learning algorithms in browser extensions for malware detection, it has also pointed out several areas for improvement. By improving the limitations in this experiment and incorporating user suggestions, future editions of this project will become a more user-friendly and effective measure to ensure that internet users are protected from cyber threats that continue to evolve.

8.0 Conclusion and Future Work

This paper designs and evaluates a browser extension that incorporates supervised machine learning algorithms in such a way that malicious links related to downloadable media content can be identified and mitigated effectively. In respect to the research questions were: How can a browser extension be utilized effectively to identify and mitigate risks associated with malicious links? How does integrating supervised algorithms enhance malware detection performance?

We have succeeded in developing a browser extension that performs URL classification using various machine learning models (DNN, SVM, RF) with real-time malware detection. The results demonstrated that DNNs classify very accurately both known and novel threats: macro average precision of 0.96 and recall of 0.89. These results thus show the power of using machine learning with a browser extension, which falls in line with previous work that has shown this approach has several potentials. This work contributes to increasing online safety in an evermore complex cyber threat landscape.

This browser-based extension offers a much more proactive solution with real-time functioning and adaptability to user interaction, filling the deficiencies of traditional antivirus software that mostly rely on reactive measures. However, the study also exposed limitations to the potential production of false positives and continuous updating of machine learning models to keep pace with the threats in evolution. Looking ahead, some meaningful avenues for future work can be identified. One such avenue could be the integration of unsupervised and reinforcement learning techniques into the detection algorithms for improved adaptability. If we let this model learn from new data without explicit labeling, then it would greatly help improve its identification of emerging threats and reduce false positives. Such studies should also be repeated over time to establish the continued effectiveness and user acceptance of the browser extension in varied everyday settings. This may also involve commercialization of the browser extension so that it can be used by all internet users. This development for a user-friendly version would increase online security. Such collaboration with cybersecurity firms in integrating this technology into existing security solutions would help spread the use in all spheres.

In other words, while this research has traveled a considerable distance in answering the research question and meeting its objectives, it also offers immense scope for further research and refinement. In a future study, building from the findings of this research and learning from the limitations, further advances within the malware detection arena could be made to ensure a much safer online experience for end-users across the world.

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