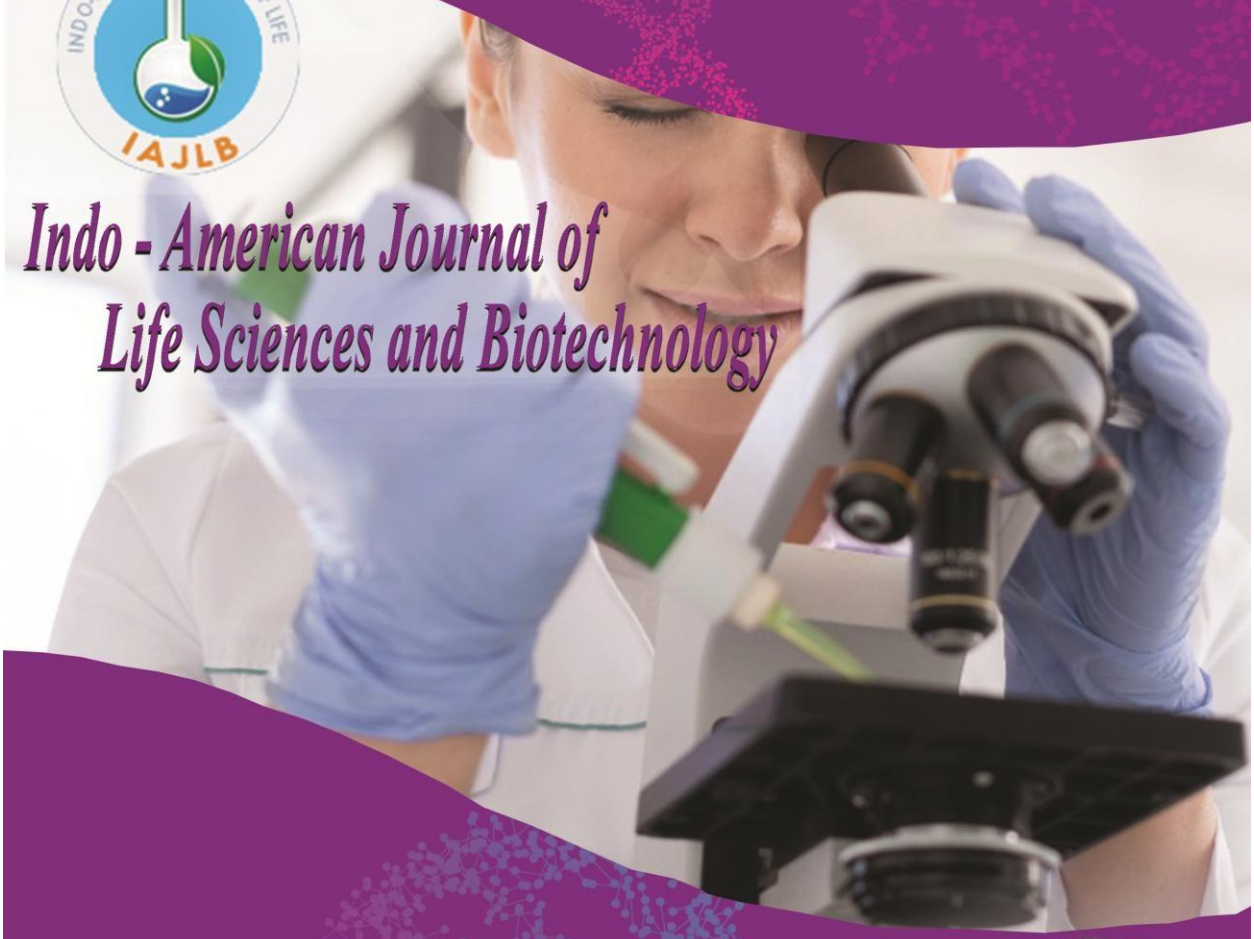
ISSN : 2347 - 2243

Indo - American Journal of Life Sciences and Biotechnology



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Indo-Am. J. of LifeSc & Bt., 2021 *ISSN 2347-2243 www.iajlb.com*

Indo-American Journal of Life Sciences and Biotechnology

Vol. 18 Issue. 3, Aug 2021

Real-Time Mobile Malicious Web pages Detection Using kA YO

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Abstract:
The content, appearance, and practicality of mobile web sites are strikingly different from those of their desktop counterparts. Consequently, current methods for detecting fraudulent websites are unlikely to be able to adapt to these kinds of situations. kAYO, a mechanism for distinguishing between malicious and benign mobile websites, is the framework we use to build and implement this system. KAYO's guarantee is based on the quantity of iframes on a website, as well as the proximity of world-renowned deceptive phone numbers. Before we can discover which current static elements are most closely associated with malicious mobile web sites, we must first show the technical requirements for mobile-specific approaches. A dataset of more than 350,000 harmful and benign mobile web pages is then used to show 90% accuracy in kAYO classification. Google Safe Browsing didn't identify these sites, but kAYO did, and we defined and reported them. A browser plugin for kAYO is also in the works to keep consumers safe from fraudulent mobile websites. Thus, we offer a fundamental static analysis method for detecting malicious mobile web pages.

1. INTRODUCTION:

MOBILE devices are more and more being employe d to access the web. However, in spite ofgreatadvances in The surfing experience on a mobiledevice is drastically different from that on adesktop or laptop computer.

Accordingly, these changes will be mostly blamed on mobile web sites' dramatically reduced screen size, which has a significant influence on the content and style of these pages.

Desktop area content, practicality, and layout may often be analysed using static analysis [1–3]. Malicious intent has previously been shown by indications like iframe frequency and redirection frequency. As a result of the many alterations brought forth by

On the other hand, we may assume that the There are no surprises here.

It was impossible for anything that had been built to be true any more. When comparing, for instance,

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Many normal innocuous mobile web sites need many redirects before visitors obtain access to information, and such behaviour would be recognised as suspicious in the desktop configuration. In addition, previous methods neglected to account for mobile-specific homepage components such as calls to Mobile APIs.. An excellent example of this is a link that launches the phone's dialer. In order to detect harmful sites on the mobile internet, new technologies are absolutely essential.

When it comes to harmful mobile web sites, kAYO is an excellent static analysis tool that can be used in a matter of minutes. Mobile web pages' markup language and JavaScript content, the computer address, and enhanced mobile-specific capabilities are all used by KAYO to provide static alternatives for static mobile web sites. It is our practise to begin by experimenting and demonstrating that the distributions of similar Static characteristics, once retrieved from desktops, have a true positive rate of 89%. kAYO's performance is comparable to, or perhaps better than, that of current desktop approaches. KAYO also discovers a number of harmful mobile sites that aren't caught by conventional approaches like malware Total or Google Safe Browsing. As a last step, we prefer to explore the limits of current tools for observing mobile harmful websites and create a browser extension supported work over that delivers real-time feedback to mobile browser customers.

Wecreatethesubsequentcontributions:

Demonstrate the differences between desktop and mobile Web page "security features" using an experiment: Static choices employed in current methodologies are completely different when tested on mobile and desktop web sites, according to one experiment. Furthermore, we tend to show that some choices are either connected or unrelated or non-indicative of a website being malicious when pulled from all areas of the site.. Our tests have shown that malicious web sites targeting law enforcement need mobile-specific approaches.

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2. Identify and construct a classifier for malignant and benign mobile sites, as we gather over 350,000 of each. These new static characteristics are then used to differentiate between mobile benign and malicious websites. Classification accuracy is up to 90% thanks to the extra work, and mobile websites differ fairly from desktop webpages. Over the course of three months, we collected over 50,000 mobile dangerous and benign websites. With this binomial classification strategy, we can produce an algorithm for fast feature extraction with 90% accuracy, which is two orders of magnitude faster than equivalent current algorithms already in use for feature extraction. Additional evidence of the significance of kAYO's alternatives may be found via empirical investigation.
3. A total of 173 mobile websites based on cross-channel assaults, which are aimed at making mobile users choose phone numbers associated with known fraud schemes, have also been identified.
4.
5.The following features should be implemented in a kAYO-compatible extension: Static analysis's first method for detecting mobile-specific malicious websites is knock cold, to the best of our knowledge. There don't seem to be any existing technologies, such as Google Safe Browsing, enabled on mobile devices, thereby preventing their usage.
6.
7.Another advantage of this method is that it can identify fraudulent mobile websites that are now incomprehensible by present tools. Firefox desktop browser extensions show that there is a lack of solutions to assist in the identification of harmful mobile websites. Firefox mobile browser addonkAYO used for this purpose, which warns users of the malice they would encounter in a certain time. After publication, we want to make the extension publicly available.
8.

9. For example, earlier static detection literature [1], [2], [3] has used the term "venom" to describe a venomous substance. Drive-by downloads are not popular in the mobile home at the time of this writing, hence the vast majority of discovered sites are phishing-related.

10. RELATEDWORK:

Techniques for detecting fraudulent websites based on content and in depth examination: Virtual machines are being abused by dynamic techniques. One, four, and honey client systems are all examples. Dynamic techniques may be more difficult to measure because of [5], [6], and [7].

Mistreatment of static techniques may avoid this performance cost. When using a static method, you rely on the page's structural and lexical qualities rather than its actual content. Malicious URLs may be tracked down using a variety of methods, one of which is the use of mathematical methods to identify the lexical and host features of a URL [8, [9], [10], [11].

URL-based approaches, on the other hand, have a high likelihood of false positives. With HTML and JavaScript choices taken directly off of a site and combined with URL categorization, it is possible to overcome this drawback and get better results. It is possible to avoid the performance cost of dynamic techniques by using static approaches instead. When using rapid and dependable static ways, you may avoid expensive in-depth study of all web pages by using these methods.

Mobile and desktop websites have distinct features that make it difficult to use these methods to identify fraudulent webpages. When it comes to web security, mobile browsers differ from their desktop counterparts [15, 16]. It's not apparent how differences between desktop and mobile websites affect security, despite the fact that they've been identified previously [17]. As a result, the dangers on mobile and desktop websites are somewhat distinct. Drive-by downloads on desktop websites are largely examined using static analysis methods [1], [2], but phishing is now regarded to be the most significant issue on the mobile internet [19]. Anti-phishing efforts include uninflected browser programmes of varied trust levels, email screening, and the maltreatment of material on a webpage. A low false positive rate means these systems are also accurate.

Each webpage's performance is impacted by downloading or capital punishment, as well as based choices [12, 13, and 21]. For spotting phishing websites, Cantina [12] is the most known non-proprietary technique. Anguish is felt by Cantina

performance concerns stemming from a pause in Google search queries. In addition, Cantina doesn't operate properly on non-English websites. Existing methods do not account for emerging dangers, such as well-known scam phone numbers that are set to activate the phone's caller ID.

It remains to be seen whether static analysis methods used to detect fraudulent desktop websites can be used to mobile websites, as well. In the last several years, significant progress has been made in the field of mobile application security. One of the most important early areas of study was static feature extraction, especially in relation to permissions [22], [23], [24], [25]. Using these methods, rogue programmes in a variety of markets may be detected much more quickly and reliably. To find malicious domains, one of the most common methods used by law enforcement to investigate online crime is based on the use of DNS-based methodologies. Active DNS inquiry methods [30], [31] as well as passive DNS monitoring ([26], [27], [28], [29]) have all been used to identify rogue domains. Another [27] may even uncover sites implementing phishing and drive-by downloads, but some of these initiatives focused only on police investigation fast flux service networks [30], [32], [33], [34]. The activity imposed by a website or domain can't be gleaned through DNS-based techniques.

11. MOTIVATION:

Web page choices like HTML, JavaScript, and URL attributes are often used in static analysis approaches to identify fraudulent websites. In most cases, these alternatives are provided to machine learning algorithms to categorise benign and malicious websites, respectively. According to these methods, there is a perception that the choices are dispersed differently across both legitimate and malicious websites. Since static options distribution affects categorization findings, any modifications to benign or harmful websites that are made have an influence on the distribution of static options These static analysis methods are useful, but they've only been applied to desktop websites [1], [2], [12]. In terms of content, practicality, and layout, mobile websites are very different from their desktop equivalents. In order to detect fraudulent desktop websites, present technologies rely on static parameters that are unlikely to be used on mobile webpages. We believe that there are four reasons why distinct static analysis approaches should be used to monitor dangerous mobile sites.

Mobile websites tend to be simpler than their desktop equivalents in terms of content. As a result, the dissemination of content-based material

When it comes to static settings (such the number of JavaScripts) on mobile websites, they vary from those on desktop websites. For example, the normalised density of iframes and the quantity of Javascripts discovered in mobile2 and the matching desktop versions of Alexa's 10,000 most popular websites [35]. iframes are absent from around 90% of mobile websites, whereas they are present on the matching desktop percentages.

Multiple iframes may be seen on a same site. There are more JavaScripts on desktop sites than there are on mobile ones. With the ease of mobile sites, the bulk of additional content choices, such as the number of photographs, page length, hidden sections, and the number of parts with a small amount of space, all take problem in both mobile and desktop webpages. Web site providers employ JavaScript or user agent strings to identify and route mobile visitors to a mobile-optimized version of their sites. There are several redirection on even the most well-known mobile websites, which has traditionally been a trait of malware-hosting desktop websites [1]. Due to their hosting architecture, mobile websites are more likely to have many redirects than their desktop counterparts. Not all static choices used in current methodologies change when assessed on mobile and desktop websites, as we've seen in the past. There is a similarity in DNS server responses for mobile and desktop versions of the same website, for example. The hosting infrastructure for mobile websites seems to be the same as that for desktop websites [36]. DNS addresses given by seven public DNS servers (including Google's own and those run by OpenDNS and Scrubit) were utilised to compile this report. Records of URLs for mobile and desktop computers

of the top 10,000 Alexa-ranked websites. The seven DNS servers provide identical distributions of information processing addresses for mobile and desktop websites.

A smaller display than a personal computer has a big impact.computer. Consequently, a mobile user only sees a portion of the computer's URL. One would assume that in order to fool a mobile phone user, the creator of a mobile phishing website merely has to include misleading terms in the computer URL at the beginning.

TABLE 1
The 44 Features of kAYO from Four Categories

Category	Features	Total # of features
Mobile specific	# of API calls to tel:, sms:, smsto:, mms:, mmsto:, geolocation; # of apk, # of ipa	8
JavaScript	presence of JS, noscript, internal JS, external JS, embedded JS; # of JS, noscript, internal JS, external JS, embedded JS	10
HTML	presence of internal links, external links, images; # of internal links, external links, images # of cookies from header, secure and HTTPOnly cookies, presence of redirections and iframes, # of redirects and iframes, whether webpage served over SSL, % of white spaces in the HTML content	14
URL	# of misleading words in the URL such as *login* and *bank*, length of URL # of forward slashes and question marks, digits, dots, hyphens and underscores, # of equal signs and ampersand, subdomains, two letter subdomains, semicolons, presence of subdomain, % of digits in hostname	12
	Total:	44

These mobile-specific features are not included in the feature set of analysis methods. Mobile-specific functions can help us identify new risks in an online environment that is always changing.

As an example, if a well-known 'bank' fraud variant is found on a web site, it may imply that the site is an imposter of the same bank. [37]

There are certain limitations to current methods: An inquiry is needed into these disparities between mobile and desktop sites. Static analysis approaches and tools for detective work on fraudulent websites are aimed for desktop webpages currently available. The result is that mobile-specific hazards cannot be accurately observed. Secondly, many mobile-optimized websites produce empty pages when viewed on a desktop computer. Even current dynamic analysis methods that run webpages in desktop browsers on virtual machines may be used to analyse data.Using a computer on a mobile website is useless. For the time being, signature-based technologies like Google Safe Browsing can only be used on PCs. From the Google Chrome browser on a mobile device, we saw five mobile-specific malicious URLs acquired from PhishTank [38]. (in Table 1). Chrome's desktop version does not identify these sites as malicious, but Chrome's mobile version does, and it is these people who are the primary targets of mobile harmful webpages. Google Safe Browsing on mobile Chrome is a technical effort, but we often argue and illustrate that a mobile-specific static method may also find new risks previously missed by such services.For this project, the aims are three-fold in light of the limitations of current methodologies. In the first place, it's necessary to tell useful static alternatives from from crazy mobile particular websites. Secondly, a rapid and dependable static analysis implementation techniquetodiscovermaliciousmobilewebpagesi nreal-time.Andfinally,developingamobilebrowserexte nsion thatwill examine mobile webpages inperiodoftimeandsupplyfeedbacktotheuser.

12. METHODOLOGY:

Our goal is to build a real-time mechanism for identifying dangerous mobile websites. Websites may be classified as harmful based on their static properties. kAYO's feature set is initially discussed, followed by the data collecting procedure.

kAYOFEATURESET:

HTML and JavaScript code, graphics, the URL, and the header are all part of a website. Applications operating on a user's device using the net arthropod genus are accessed by mobile-specific websites as well (e.g., the dialer). To build the feature set for kAYO, we use these components' structural, lexical, and quantitative aspects. Extracting mobile-relevant alternatives with the shortest extraction time is our specialty. Our belief is that these features are strong indications of whether or not a website has been built for the benefit of the user or for malevolent intentions.

For our feature set, we've included forty-four possibilities, eleven of which are brand new and have never been seen or utilised before. Our descriptions of these new choices tend to be fairly detailed. Alternative writers have used a collection of beat choices in static WebPage examination in the past. However, it is important to note that these choices varied in magnitude (e.g., the range of iframes) and exhibit variable association with the character of the site (i.e., malicious/benign) in mobile and desktop browsers. Mobile specific-, JavaScript-, hypertext mark-up language-, and address choices are divided into four categories in kAYO. When it comes to mobile-specific features, we're the first to adopt them and don't claim uniqueness by repurposing previously available choices in new ways. There are eight mobile choices, ten JavaScript options, fourteen HTML options, and twelve address options summarised in Table 1.

It's all about the mobile features.

You may get a sense of the advanced capabilities of mobile websites by collecting eight mobile-specific characteristics

Websites for smartphones and tablets. Dialer and SMS apps are spawned several times on mobile devices through mobile web APIs such as tel: and sms:. Mobile API calls were studied by extracting the total number of API calls from each mobile site. From these API requests, we were able to further retrieve the intended recipients' phone numbers. Every signalling was subjected to the commercially available Pindrop Security Phone Reputation System (PRS) [39]. In the PRS findings, we prefer to give every phone number scraped from the mobile API calls a score of 1/0 (known fraud/benign) and other the score as a feature in kayo. All of the numbers we gathered had the API prefixes that might be used to activate an app installed on a user's phone. We didn't thought about signalling strings posted on websites without the prefix of an API. We believe that a website that hosts its own mobile application binary (e.g.,.apkor.ipa files) promotes hazardous behaviour because of the recognition of application stores like Google Play and iTunes. There are numerous third-party app stores out there, and if we see a large number of files (in the tens of thousands) on the same website, we tend to think it is safe.

Features of JavaScript:

With JavaScript, you may interact with users on the client side, communicate asynchronously with servers, and make changes to the DOM objects of websites as you go. To capture the JavaScript relevant static behaviour of a site, we typically extract 10 choices, including two brand-new ones Only JavaScript deobfuscation-enabled settings are faster to extract. Malicious websites often use obfuscated JavaScript. Instead of decoding each JavaScript one by one, we extract the simplest possible version.

Using JavaScript, you may access menu items on a website. To begin, this method was chosen because, as shown by yue et al. [40], a large number of websites include what seems to be harmful JavaScript code. As an instance, 44.4% of the top 6,805 Alexa-ranked sites make use of the possibly harmful eval function. Existing methodologies [2] have led people to believe that bad websites typically include potentially harmful JavaScript phrases. These findings prove the opposite is true. Secondly, external JavaScript files may be rather large, on the order of a few gigabytes at the most. megabytes. Our ultimate objective is to create a rhythm that is supported by a period browser plugin.

Therefore, we avoid characteristics that would slow down the feature extraction process. It's thus common practise for us to verify whether or not a website contains external or internal JavaScript, then extract the quantity of both internal and external JavaScript from a given web page. Embedded JavaScript is different from both internal and external JavaScript in that it is part of the site itself. Embedded scripts are faster to load than externally referenced scripts when the number of Java-Script lines is small. As a consequence of this, the application software must make a separate call to the web server to get the external code since it encounters the relevance of the external code when loading the page. In order to optimise a website's speed, JavaScript is often integrated. The mobile web's performance is critical since it affects both income and user interest [41]. As a result, we check to see whether a website has embedded JavaScript and so compute the amount of embedded JavaScript on a webpage. The following are some of the HTML features: From the markup language code of every website, we derive a total of fourteen alternatives for you to choose from. In order to provide a better user experience, most websites now include a broad range of images as well as links in both internal and external markup languages. On the top-ranking page of m.cnn.com, for example, there are links to various CNN news pieces, adverts for an area building, and images linked with the most recent breaking news. As a result, we initially check to see whether a page has any pictures,

internal and external markup language connections, and other relevant information. kayo characteristics include the number of internal links, external links, and pictures found on a certain page.. Links to harmful information may be found in iframes on malicious websites (particularly those that use clickjacking and drive-by-downloads). On mobile websites, the placement of iframes is completely different than on desktop websites. The existence and variety of iframes in an extremely website are alternatives in work over, and we don't rule out a harmful mobile webpage or dangerous material in iframes. Past

According to an investigation, rogue websites utilise a series of redirects before delivering the visitor to their intended destination [1]. Remember that mobile websites often need at least one or more redirections since the desktop and mobile versions of the page use the same hosting infrastructure. As a result, we check to see how many redirects a visitor has to go through before arriving at the final URL to see whether a page was really redirected. Last but not least, we determine the HTML script's white space %, the header's cookie count (including secure and HTTP Only cookies), and if the site is provided over an SSL connection. To have a better understanding of the value of these HTML properties, readers should consult past research [2], [12], [14].

Features of the URL:

A URL's structure and lexical features are familiar to malicious and non-malicious websites.

Victimizing just URL alternatives for this kind of difference, on the other hand, results in a large proportion of false positives. We tend to extract twelve URLs in total. Fraudsters employ terms in the URL to trick people into thinking the phishing site is the real thing, which is how they convince their victims to click on their links. There are a lot of websites out there that include words like "login" and "bank" in the URL of their login page since they're so easy to copy. Due of the small screen size, just a portion of the URL may be seen by a mobile phone user [15].

To put it another way, phishing website authors may use dishonest terms at the beginning of their URLs because of this. This is a brand-new feature in kayo, therefore the inclusion of these terms in the URL is something we take for granted.

There are several phishing domain names that simply point to a computer that hosts them [9, 43]. In order to figure out the number of digits in a Uniform Resource Locator and the percentage of digits in a hostname, we computed both. In order to add misleading terms such as "paypal" as a subdomain, phishing website developers often construct a range of subdomains. The length of phishing URLs may rise as a result of this. We thus include the URL's length, regardless of the URL's content.

dot choices for subdomains, the number of subdomains, and so on Besides the number of semicolons, equal signs and punctuation symbols in our URLs, forward slashes and question marks are also part of our URL feature set. For further information on the relevance of these URL choices, interested readers may refer to earlier publications [8], [9], [44]. However, it's worth noting that the markup language, JavaScript, and URL choices aren't particular to mobile and may be used for analysing desktop websites. However, desktop websites cannot take use of mobile capabilities like dialer and SMS, which are included in mobile programmes.

COLLECTING INFORMATION:

As part of the data collection procedure, we collected mobile-specific websites classified as benign or harmful.

Before we get into the specifics of how to identify and define "mobile-specific websites," we outline a practical experiment. The data gathering procedure will take place over the course of three months in 2013. For this reason, we select these crawls since they are as near to an exact match as possible to the original work.

THE DEVELOPMENT PROCESS AND ITS EVALUATION:

This section explains the machine learning approaches we used to address the challenge of identifying mobile-specific websites as either dangerous or harmless. To ensure that our model is accurate, false positive and true positive rates are evaluated. Finally, we establish the importance of kAYO's properties experimentally by comparing it to other methodologies. If automated analysis is practicable, we utilise our whole datasets; but, when considerable human analysis and verification is required, we employ randomly chosen portions of our data.

MODEL AND APPLICATION

When it came to spotting rogue websites, we approached it as a problem of binary classification. Negative and positive samples were defined by the presence or absence of known harmful mobile webpages. As far as binary classification approaches go, we looked at a broad range of common alternatives, except for space. SVM, naive Bayes, and logistic regression are all examples of support-vector machines.

Support Vector Machines (SVMs) are a binary classifier that might be widely used. On the other hand, it only works well with a few thousand samples. SVM was not the best option for kayo because of its scalability limitation and our large dataset. As soon as the values of several attributes are reciprocally free, nave bayes is most often utilised. Many of the alternatives we drew were interdependent. Our model's internal, external, and embedded JavaScript choices all had an effect on the number of scripts that appeared on a given site. Naive Bayes couldn't be used since the assumptions required for balanced performance failed to hold in our dataset. An ascendable classification approach, logistic regression does not make any assumptions about the distribution of feature values. The results of this analysis show that this strategy was the best match for our data. To prevent overfitting of the data, we used '1-regularisation in conjunction with the binomial variation of logistic regression to model kayo.

We dynamically crawled the obtained mobile URLs from each input pages using the scrapy [52] web scraping tool. Python was used to enforce the crawler and extraction routines. For training and testing, we employed supply regression on the extracted choices. Octave, a numerical programming language, was used to create our logistic regression model [53]. In order to evaluate the model, we ran it on an eight-core, quad-core Intel Core i7 CPU, and 16GB of RAM.

Mobile web pages are very different from their desktop counterparts when it comes to analysis. By imitating the features that we often regard to be reasonable indications of a reputable website, kAYO will not be defeated by this tactic. It is possible to successfully dodge kAYO, as shown by our examination of a huge dataset. We crawledAlexa's top million most popular websites. Thus, we were unable to compile a list of websites using JavaScript.

observe and direct to the mobile webpage. we'vealso missed the mobile webpages diagrammatic bywaysotherthanthose utilizedbythe top 1,000websites.

We do not make any claims regarding gathering allmobilewebpagesfromAlexahighamillion.However,giventhemassivesetofwebpagescollected, we believe that our dataset could be arepresentativecrosssection.Finally,themaintargetof this work was on mobile webpages designed forphones. we have a tendency to defer the analysis ofwebpagesdesignedfortabletstofuturework.kAYO’s features mirror current trends in mobilemaliciouswebpages.Thepotentialofdangerousactivitywithinthemobilenetcouldincreasenevertheless additional over time. kAYO’s featureset and model will need to be updated, in line withthe new threats faced by the mobile net within thefuture.

However, such updates area unit necessary all toldstatic techniques that aim to detect new threats. In-depth dynamic analysis of web pages might giveadditionalnecessarydetails.However,asaresultofsuch approaches incur considerably higher

prices,thisapproachconflictswithourstylegoalof makingatimeperioddetector.

Accordingly, we leave the numerous challenge ofecoKeep an eye on and divert your attention to the mobile website. Aside from those used by the top 1,000 websites, we haven't seen any diagrams for mobile websites.

We do not claim to have gathered all of Alexa's million-plus mobile pages. Despite this, we feel that our data collection represents a cross-section of the web in general. Finally, the focus of our research was on creating mobile-friendly websites. We tend to postpone the study of tablet-optimized websites until a later date. Current developments in mobile harmful websites are reflected in kAYO's design elements. The dangers of using the mobile internet might become much more in the future. New dangers to the mobile net will need changes to kAYO's features and business in the future.

All static strategies to identify new threats need such updates, though. An in-depth dynamic examination of web pages might provide extra information. However, this technique contrasts with our design aim of creating a time period detector since it incurs much greater costs.

As a result, we defer to future researchers the many challenges of making these technologies economically viable. To evaluate in real-time using kAYO. Performance magnifying designs that maintain real-time analysis are going to be investigated in the future.

In terms of substance, practicality, and layout, it is superior than its desktop equivalents. As a result, conventional strategies for detecting fraudulent activity on desktop websites are ineffective on mobile websites. kAYO, a rapid and reliable static analysis approach, was devised and developed by our team to identify malicious mobile websites. In all, kAYO measures 44 mobile-related choices from websites, of which 11 are newly discovered mobile-specific options. With a classification accuracy of 90%, kAYO finds a wide range of harmful mobile sites that aren't picked up by other methods, such as Google Safe Browsing and VirusTotal. We end up creating a browser plugin that provides real-time feedback to users using kayo software.

In our conclusion, we show that kayo can identify new mobile-specific dangers, such as websites that carry significant content.

The first step in identifying new cyber security threats in the modern world is to pinpoint the nomadic functioning of these technologies for future research purposes. To evaluate in real-time using kAYO. Performance magnifying designs that maintain real-time analysis are going to be investigated in the future.

In terms of substance, practicality, and layout, it is superior than its desktop equivalents. As a result, conventional strategies for detecting fraudulent activity on desktop websites are ineffective on mobile websites. kAYO, a rapid and reliable static analysis approach, was devised and developed by our team to identify malicious mobile websites. In all, kAYO measures 44 mobile-related choices from websites, of which 11 are newly discovered mobile-specific options. With a classification accuracy of 90%, kAYO finds a wide range of harmful mobile sites that aren't picked up by other methods, such as Google Safe Browsing and VirusTotal. We end up creating a browser plugin that provides real-time feedback to users using kayo software.

In our conclusion, we show that kayo can identify new mobile-specific dangers, such as websites that carry significant content.

The first step in identifying new mobile internet security concerns is to identify fraud numbers.

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