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Performance Evaluation of Websites Using Machine Learning

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Dedication

I dedicate my thesis to my family. A special feeling of gratitude to my loving parents, whose words of encouragement and push for tenacity ring in my ears, and who never left my side and are very special. I also dedicate this dissertation to my beloved wife, and I will always appreciate her patience, encouragement and all she has done for me. I also dedicate this dissertation to my brothers, sister, my children and friends who have supported me throughout the process.

Thank you all

Mohammad Rebhi Rateb Ghattas

Declaration

I certify that this thesis submitted for the degree of Master is the result of my own research, except where otherwise acknowledgment and that this thesis or any part of the same has not been submitted for a higher degree to any other university or institution.

Signed: ....

Mohammad Rebhi Rateb Ghattas

Date: 23 June 2019

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Abstract

The Web is playing a major role in various application domains such as business, education, engineering, and entertainment. As a result, there are increasing interests in designing and developing an effective website to deliver a high degree of performance. Therefore, automated support for web designers is becoming more important to evaluate websites performance. Hence, many of the previous studies tried to evaluate websites performance by developing a static model and it's unless used for more domain.

The aims of this thesis are: (i) to explore the best metrics that most affect website performance; (ii) propose a dynamic model for performance evaluation of websites by using machine learning that called is PEML ; and (iii) to help webmaster and decision-makers to know what improvements are needed to enhance the performance and the final relative weights of metrics in the level of the hierarchy.

This research proposes a dynamic model to performance evaluation of websites using machine learning method by applied two regression methods experiments namely, multiple linear regression and support vector machine regression on the same dataset that collected, to take the best performance of regression methods to generate weight for every metric and then developing a new dynamic model to evaluate websites performance.

Keywords

website performance, regression, machine learning, web metrics, support vector machine, multiple linear regression, evaluation, RapidMiner.

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List of Abbreviations

Abbreviation	Abbreviations Full Name
LR	Linear Regression
SVM	Support Vector Machine
LWM	Linear Weightage Model
AHP	Analytical Hierarchy Process
FAHP	Fuzzy Analytical Hierarchy Process
RP	Rapid miner

Chapter 1

Introduction

This chapter introduces the thesis. It describes the problem statement, purpose, research questions, limitations, contributions, methodology and organization of the thesis.

1.1 Research Overview

Lately, we have got become witness to an important alteration of our lives to a worldwide with the incipience of the web era. The web is an increasingly more vital asset in many sides of life: government, education, commerce and more [3]. Hence, Websites are a key element in obtaining the right information about the institutions. However, when it comes to a huge number of synchronous users these websites performance decreases considerably.

Utilizing the web devices many institutions become been able to raise their being customer-focused and their attributes of services and products. The analysis of the web site is currently thought to be an essential facet of attracting customers' attention[3]. In this study, it is logical to explore metrics into measure the performance of websites, whether to study the communication efficiency that they represent or in order to build useful appraisal metrics.

As result of the above requirements, it is important to provide a method to evaluate the performance quality of websites which include various technological and logical factors. Each definition of performance quality from literature leads to lists of criteria about what constitutes a good quality website and how to measure the performance [8]. Therefore, it is important to build a model into evaluation websites performance, thus ensuring the development of modern websites and keeping abreast of modern technology.

This study employed machine learning to build a mathematical model approach to evaluating the performance quality of websites. In this thesis, we suggest an method based on appropriate metrics for evaluating websites performance.

This study proposed to build an understandable and applicable dynamic model for evaluating websites performance by using previous studies as a case study. By establishing a practical model, it is expected that organizations can better understand whether a given website can meet the expectations of its users, they serve in order to grow their satisfaction level.

1.2 Problem Statement

The website is becoming more important each day for conducting business, sharing information, and communication. Each passing day, the number of organizations, companies, and individuals propagation their websites is increasing.

Hence, the task of evaluating and improving the websites can be intimidating, considering the number of websites available, and the frequency of updates. As a result, automated support for web designers is becoming more important to evaluate websites performance. It is necessary to provide an easy method to performance evaluation of websites, which include several technological and logical factors, as a contribution to addressing this need.

Therefore, the problems in this study are : How to determine the best metrics that affect websites performance, what are the weights of every metric of website performance, how can arrangement for metrics that more affect websites performance in the level of the hierarchy, and how to evaluate the performance of the proposed approach.

1.3 Research Purpose

Due to the currently limited number of studies evaluating websites performance, we want to set an example for similar research in the future through the website evaluation by using machine learning. The goal of this study is to gain a wide understanding of evaluating websites performance.

We have three sub-purposes for this study. Firstly, we want to investigate the metrics of evaluation for websites. Secondly, we want to collect data and creating the dataset. Third, we want to determine the method by using the machine learning to extract weight for every metric. Finally, we want to build a dynamic model for website evaluation, to inspire other researchers in evaluating websites.

1.4 Research Questions

We have formulated two research questions based on research purpose stated above:

1. What are the best metrics to evaluate websites performance?
2. How can webmaster benefit from the metrics in the level of the hierarchy to enhance the website's performance?

During the study, we will answer these two questions (chapter 5).

1.5 Research Limitations

In the research, we have some limitations such as:

- Identifying the metrics that affect the performance of the websites.
- Considering, only, the selected websites in several domains, such as: (Business, health, government, and education).

- Lack of tools for collecting data to develop the model in order to evaluate website performance.

1.6 Research Contributions

If we want an efficient website, we must test its performance. Also, we should mention, that if no one has complained about the website, it doesn't mean that all your visitors are using your site effectively, and to their full satisfaction. But manual performance testing (by a human) requires a lot of time, effort, and it lacks accuracy. Hence, many of the previous studies tried to evaluate websites performance by developing a static model [3] [8] [9]. Therefore we want to propose a new methodology for evaluating websites using machine learning to build a dynamic model to evaluate websites performance. And help the designers to enhance website performance through determining metrics that best affect website performance. Finally, developing a new dynamic model to evaluate websites performance and we want called PEML Model.

1.7 Research Methodology

This study adopted quantitative research and experimental to proposes a new approach for evaluating the performance of the websites using machine learning, as follows:

- **Identification of metrics that affect the performance of the websites**: To identify the metrics that affect the performance of a website, we conducted an extensive literature review and make online survey with local experts to selected the best metrics that affect websites performance.
- **Collect quantitative data for identified metrics:** Testing of many of websites by using the online web diagnostic tools are shown in Table 4.4 which can be used to collect quantitative data for identified metrics from local experts. After that, we used

statistical tool to find the most influence metric to enhancing the website performance among all the collected metrics and rule out every metric unless has no affect website performance.

- **Determine machine learning method:** We selected regression method to predict website performance based on the dataset that is numerical and regression methods is a form of predictive modeling technique which investigates the relationship between metrics and estimates the relationship between two or more metrics.
- **Calculating weights for every metric:** We generated a weight for every metric by using regression methods. Moreover, after generated weight to every metric, we can arrange the most affect metrics on the website's performance on the level of the hierarchy.
- **Model Evaluation:** There are criteria whereby they can be evaluated and compared to take the best performance among the algorithms based on correlation, average absolute error, average relative error and time to build the model.
- **Build Model:** Developing a new model for performance evaluation of websites.

1.8 Thesis Outline

This thesis is structured as follows:

Chapter 1: Introduction: It gives an overview of the research and declares the problem statement, research purpose, questions, limitations, methodology, contribution.

Chapter 2: Background: Provides a general background of the concepts needed to understand the rest of the thesis.

Chapter 3: Literature Reviews: Reviews related works in performance evaluation of websites.

Chapter 4: Proposed Method: Proposes a new method for evaluating website performance by using machine learning.

Chapter 5: Experimental analysis and Model Evaluation: Analyzes the experimental results. In addition, discuses each experiment.

Chapter 6: Conclusion and future work: Represents conclusions for this research and future work.

Chapter 2

Background

This chapter provides a general background of the concepts needed to understand the rest of this research. It covers basic concepts of performance evaluation of websites, machine learning, and more specifically regression techniques.

2.1 Study Terminologies

In this section will describe terminologies used in performance evaluation of websites:

- Web page

  A website consists of multiple **pages**. A page is a definable unit of content in the web that can be separated from other pages. Based on the definition, content like flash animations and media files may also be defined as pages even though they differ from traditional pages [28].

- Evaluation

  Measuring websites, manually or automatically, based on assigned metrics to attain a superior website. The manual analysis includes specialists or real user testing whereas automatic assessments employ different software testing tools [10].

- Website performance

  Websites are part of our daily life and are the accustomed exchange and to convey information between user communities. Conveyed information comes in several types, languages, and forms and incorporates text, images, sound, and video meant to tell, persuade, sell, and present a viewpoint or maybe modification associate perspective or belief [21]. Thus, the task of evaluating the performance of the website rely on a group of factors that affect website' performance which called web metrics.

- Web Metrics

Palmer (2002) focused on the requirement for metrics and confirmed that metrics help organizations make more effective and successful websites [22]. A survey by Hong (2007) on Korean organizations found that website metrics enable measuring the website success. These metrics play two important roles: They determine if a website meet the users and the business expectations, and they identify website design problems [23].

The following is a brief description of the web metrics that are used to evaluate websites:

- Response Time: A Website server should respond to a browser request within certain parameters [24].
- Load Time: It is used to calculate the time required to load a page and its graphics [24].
- Markup Validation: It is utilized to assess and calculate the number of HTML errors, which exist on the website, such as orphan codes, coding errors, missing tags and etc [24].
- Broken Link: Broken links always reduces the quality of the website. Websites have internal or external links. A visitor expects the links to be valid, loads successfully to the clicked page [24].
- Design Optimization: The scripts, HTML or CSS codes optimized for quicker loading. The optimization also decreases the number of website parts such as images, scripts, HTML, CSS codes or video [24].

- Page Size: The size of the Web pages in the Website [25].
- No. of Request: The number of request/response between a client and a host [25].

2.2 Machine Learning

Lately, machine learning has been exceedingly used in different fields, including computer science, medicine, sports, etc.. So many applications and services using machine learning technology to solve problems. For example, email services use machine learning to filter messages spam, classify emails into important or not and recommend ads. Another machine learning technology that is widely used in social media sites is face recognition. Face recognition technology is capable of identifying persons in a given digital photograph. Today, Facebook uses face recognition to automatically suggest tags for friends in images [26].

Machine learning is outlined as "a mechanism for pattern search and building intelligence into a machine to be ready to learn, implying that it'll be ready to do higher within the future from its own experience" [26].

Hence, machine learning programs utilize example data or past experience to make the best model performance. In machine learning, the model is outlined based on some metrics, then this computer program is executed to most effective use of model metrics using the training data or past experience (the learning process). Machine learning models can be classified into predictive, descriptive or both. Predictive models make future predictions while descriptive ones gain knowledge from data [27]. As shown in figure 2.1, machine learning algorithms can be arranged into five subfields. The following subsections describe each subfield.

2.2.1 Supervised Learning

Supervised learning is the most typical kind of machine learning. In supervised learning, labeled training data is used. The algorithm makes a model from training data that can be utilized to predict hidden data labels [29]. During training, the goal of machine learning algorithms is to minify the error between output scores and actual scores. To calculate error, an objective function is used to measure the space between predicted scores and actual scores. In order to reduce error, regression adjusts its internal parameters (also referred to as weights). Weights are actual numbers that define the function which maps inputs to outputs [29].

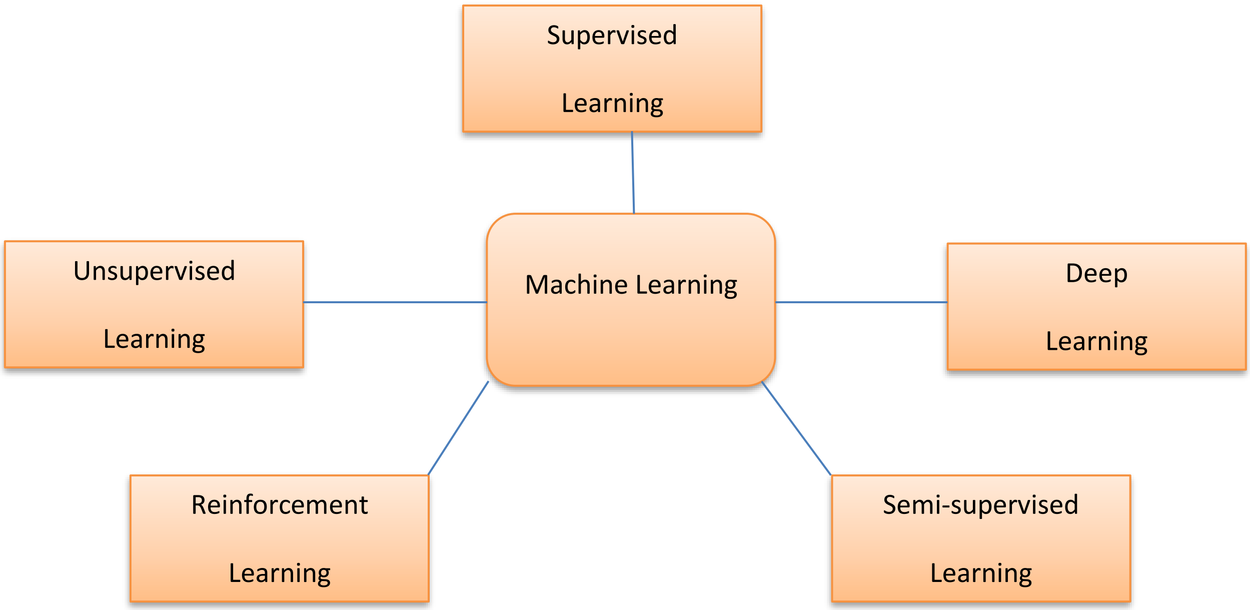


Figure 2.1: Machine learning subfields [26]

To effectively most effective use of the weight vector, a gradient vector is computed. Using a gradient vector, the learning algorithm can discover decreases or increases in error amount when changing weights which helps in optimizing weight vector values [29].

2.2.1.1 Classification

Classification is the method of classifying hidden data to a group of predefined categories. A classification algorithm uses a set of labeled training data to produce a classification model. Then this classification model is employed to predict unseen instances categories [30]. Table 2.1 an example dataset used for binary classifying customers who will buy computer and who will not. The attribute set includes properties of every client such as his name, age, income and student or not. These attribute set contains both discrete and continuous features. Thus, in classification problems the class label must be a discrete attribute [31].

Name	Age	Income	Student	Buys computer
Rami	30	High	no	No
Ahmad	35	High	no	yes
Rayyan	42	Medium	no	Yes
Khaled	38	Low	Yes	Yes
Mohammad	36	Low	Yes	Yes
Radi	30	Medium	No	No
Yousef	22	Low	yes	Yes
Sewar	42	Low	yes	Yes
Khalil	25	Medium	yes	Yes
Ahmad	33	Medium	no	Yes
Feras	33	Medium	yes	Yes
Fadi	42	High	no	No

Table 2.1: Example of datasets

2.2.1.2 Regression Techniques

In this section, we would like to explain the techniques employed in this study.

2.2.1.2.1 The Linear Regression

The linear regression type describes the output of website's performance y (a scalar) as an affine combination of the input metrics x1,x2,...,xp (each a scalar) plus a noise term ε, y=β0+β1x1+β2x2+⋯+βpxp + ε [35]. We refer to the coefficients β0,β1,...βp as the weight for every metric in the model, and we refer to β0 as the intercept term. The noising term ε for non-systematic, i.e., random, errors between the data and the model [35]. Hence, The linear regression model can namely be used for, at least, two several purposes: to describe relationships in the dataset by interpreting the weight to metrics β= [β0 β1 ... βp] T, and to predict future website performance by metrics [35].

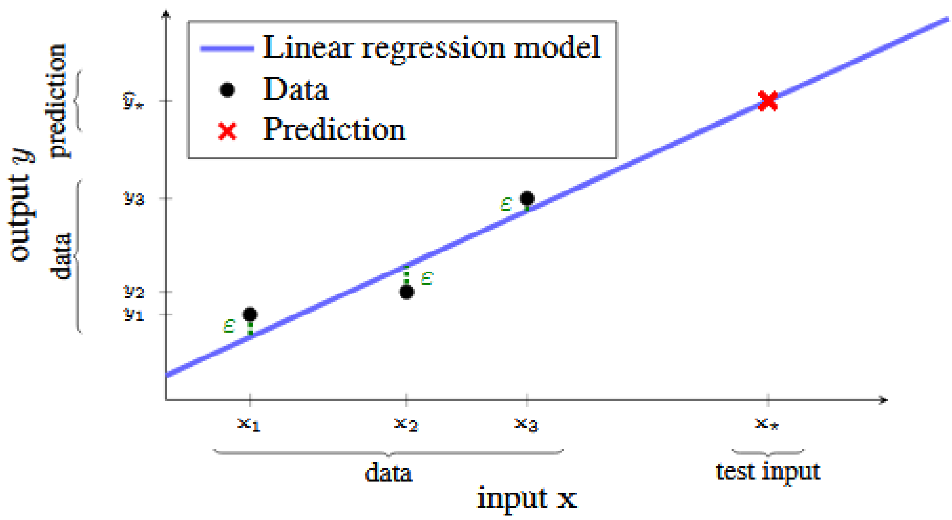


Figure 2.2 : linear regression model.[35]

To use the linear regression model, we first need to learn the unknown weight to every metric β0,β1,...,βp from a training dataset T. The training data consists of n samples of the output variable y, we call them yi (i= 1,...,n), and the corresponding n samples xi(i= 1,...,n) (each a column vector). We write the dataset in the matrix form [35]:

$$\mathbf{X} = \begin{bmatrix} 1 & -\mathbf{x}_1^\mathsf{T}- \\ 1 & -\mathbf{x}_2^\mathsf{T}- \\ \vdots & \vdots \\ 1 & -\mathbf{x}_n^\mathsf{T}- \end{bmatrix}, \quad \mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}, \quad \text{where each } \mathbf{x}_i = \begin{bmatrix} x_{i1} \\ x_{i2} \\ \vdots \\ x_{ip} \end{bmatrix}.$$

[35]

Hence, X is a ×(p+ 1) matrix, and website performance (y) an n dimensional vector. The first column of X, with only ones, corresponds to the intercept term β0 in the linear regression model. If we also stack the unknown weight to every metric β0,β1,...,βp into a (p+ 1) vector [35].

$$\boldsymbol{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_p \end{bmatrix},$$

[35]

We can express the linear regression model by two equations:

Linear regression for single metric:

$$y = X\beta + \varepsilon, \text{ [35]}$$

Multiple Linear regression for multiple metrics:

$$y_i = \beta_0 + \beta_{1}x_{i1} + \beta_{2}x_{i2} + \dots \beta_{p}x_{ip} + \varepsilon_i \textbf{ for } i = 1,2,\dots n \quad [35]$$

2.2.1.2.2 Support Vector Machine Regression

Support vector machine (SVM) may be a common machine learning tool for classification and regression, 1st known by Vladimir Vapnik and his colleagues in 1992 [18]. Support

Vector Machine can also be employed as a regression method, preserve all the main features that characterize the algorithm (maximal margin). The Support Vector Regression (SVR) uses similar basics as the SVM for classification, with only a few minor differences because the output is an actual number it becomes very difficult to predict the information at hand, which has infinite possibilities. As shown in figure 2.3 in the case of regression, a margin of tolerance (epsilon) is set in approximation to the SVM which would have already requested from the problem. But besides this fact, there is also a more complicated reason, the algorithm is more complicated therefore to be taken into consideration. However, the main idea is always the same: to minimize error, individualizing the hyper plane which maximizes the margin, keeping in mind that part of the error is tolerated [16].

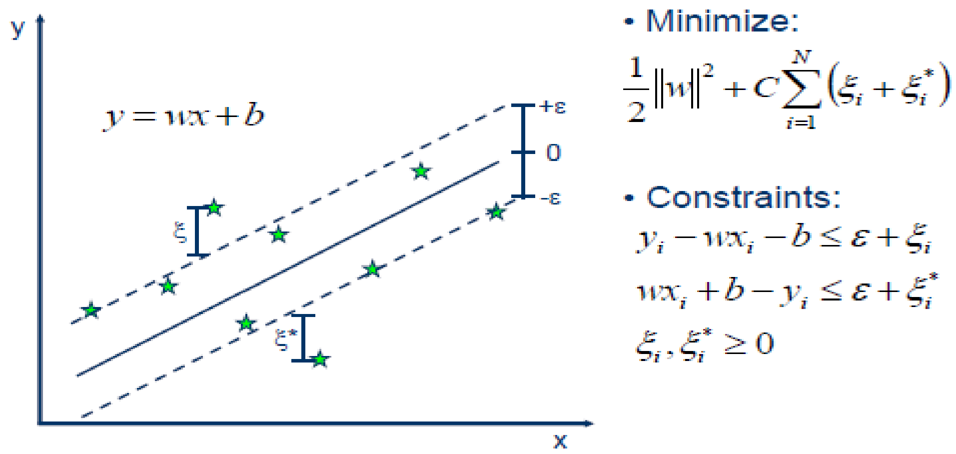


Figure 2.3 : Linear SVR [16]

we can express the linear SVR :

$$y = \sum_{i=1}^{N}(\alpha_i - \alpha_i^*) \cdot \langle x_i, x \rangle + b$$

[16]

2.2.2 Unsupervised learning

In some machine learning problems, we've got input data but we do not have particular output variables (examples are unlabeled). The main target for unsupervised learning is to search out hidden patterns and modeling underlying structure in the information. In such problems, there are no true answers and there is no teacher. Thus, the accuracy of the resulting structure cannot be evaluated [26] [32].

2.2.3 Deep learning

Deep learning is a subfield of machine learning that uniform machine learning with Deep learning works on large amounts of data which can be look as an advancement to artificial neural networks [26].

2.2.4 Semi-supervised learning

Semi-supervised learning is a subfield of machine learning that utilizes both big amount of unlabeled data and a small amount of labeled data to make a better model. Semi-supervised learning can decrease the cost associated with labeling a full training set, as labeled data often requires a skilled human agent. As an alternative, it uses unlabeled data which is relatively inexpensive to acquire [26].

2.2.5 Reinforcement learning

Reinforcement learning is a subfield of machine learning where a software agent tries to solve a problem by great as possible achievement for its actions and minimizing penalties. After a set of runs, the agent should learn the best sequence of actions that maximize the achievement [26].

Chapter 3

Literature Reviews

In this chapter, different related works are studied. The chapter is divided into Three sections, in section 3.1 we will review some related work about website evaluation studies, in section 3.2 we will present standard of the website performance, finally, in section 3.3 we will give some conclusions about this chapter.

3.1 Website evaluation studies

Lately, there is no model for evaluating airline websites, and also the existing methods do not enough understanding for airlines' proprietors to ascertain whether their websites meet the recognized guidelines from the metric of website performance. In this study, researchers have suggested a hybrid model to combine Entropy Weight Method and Grey Relational Analysis for determining and evaluating the performance of airline websites with a sample of eleven airline websites. and they have assessed many metrics of performance and each metric include design optimization, load time, response time, mark up and broken links ..etc and these metrics were measured by using on-line diagnostic tools. Vatansever et al. (2017) [3]

Kaur et al. (2016) present an empirical performance analysis of universities website that usability is currently important by website developers who will develop websites and also the performance of a website are often an important issue to its success. In this study focused methodology has been made to find all possible metrics in the website design. The researchers evaluated and compared the automated testing tools to determine their performance, speed, number of requests, load time, page size, SEO, mobile and security for university websites of Punjab [1].

Harshan et al. (2016) the active presence of library websites on the internet is becoming a hallmark of academic networks obligation to facilitate the community to access the knowledge depositories about the world. In this research the model was developed on the base of a conceptual framework, which consisted of eight quantitative performance attributes identified from an extensive literature review also as discussions with experts which include the design optimization, load time, page size, number of items, page speed, broken links, response time and mark-up validation . This study suggested a model by using AHP approach to gauge the performance of library websites. Finally, the model can be used as a guage website design guideline that helps to develop usable websites across library domains [2].

Devi et al. (2016) the main aime of this paper is to design the website evaluation framework for academic websites. The quality of an internet site makes an internet site profitable, easy and accessible, and it conjointly offers helpful and reliable information, providing good design and visual look to satisfy the user's needs and expectations. The researchers design new evaluation framework based on the main quality determinants of the chosen base model (ISO 9126-1) and rearranged to group factors with an equivalent semantic meaning in one category by removing existing repetitions and different factor names. thus, This model to evaluate the quality of websites using different quality assessment techniques starting in the earlier stages of the website design, during the intermediate design stages and the deployment stages [5].

Khan et al. (2013) this study aimed to check the Asian airline's website quality via online web diagnostic tools. The researchers used the analytical hierarchy process which generates the weights for each metrics and makes it easy to judge the better results to evaluate the website performance of each airline in Malaysia. The researchers used the metrics include Load time page size, no. of items, response time, page speed, availability, broken links, response time, mark up validation, design optimization, page rank and traffic to make the better performance website and to provide a future approach for customer satisfaction with the websites [7].

There an enormous growth of web applications and also the web applications are not simply static, document-oriented but dynamic applications with several technologies to form complex, heterogeneous web systems and applications. Many of the current website evaluation techniques and criteria for evaluating web application are unable to assess the performance and quality of web application, and most of them focus purely on usability and accessibility. And therefore, the researches presented an analysis methodology consistent with measurement approaches used in the performance evaluation domain and guideline review approaches used in the quality evaluation domain and they propose an automatic tool to calculate the quality and aesthetic factors of web application. Kulkarni et al. (2012) [6]

Dominic et al. (2011) the researchers suggested a methodology for choosing and evaluating the best e-government website based on many metrics of website performance. they used a group of metrics namely load time, response time, page rank, the frequency of update, traffic, design optimization, page size, number of the item, accessibility error, markup validation, and broken link. Thus, they proposed some methodologies for determining and measuring the best e-government sites based on many metrics of website performance, consisting of analytical hierarchy process (AHP), fuzzy analytical hierarchy process (FAHP), linear weightage model (LWM) and also one new hybrid model (NHM). This NHM has been implemented using LWM and FAHP to generate the weights for the metric which are much better and guaranteed more fairly preference of metric. and then they employ a hybrid model among linear weightage model and fuzzy analytical hierarchy process approach for the website. Then the results of this study confirmed that most Asian websites fail in performance and quality criteria. By applying the hybrid model approach [8].

Jati et al. (2011) this study applies the test to evaluate the e-government of website performance for some Asian countries by using web diagnostic tools online. they suggested a methodology for choosing and evaluating the better e-government website supported several metrics of website performance. They used the PROMETHEE II technique to get the perfect ranking of the e-government websites. Analytical hierarchy process (AHP) has been proposed for determining the better website to support researcher into the decision-making activity, that aims to determine the better website between a grouping of e-government website. The final score obtains for each website across each metric is calculated by using multiplying the weight of each metric with the weight of each website. The website which has got the highest score is suggested as the best website and decision maker may consider that one as the best decision choice. Results of the e government websites performance based on load time, response time, page rank, the frequency of update, traffic, design optimization, size, number of items, accessibility error, markup validation, and broken link [9].

Islam et al. (2011) the presented study concentrate both the user's point of view and applied automated tools to evaluate the performance of some academic websites in Bangladesh by using two on-line automated tools, such as web page analyzer and HTML toolbox were used along with a questionnaire directed to users of that websites. They used Webpage Analyzer to test the internal metrics of the websites including the total no of images, HTML page sizes, the total no of HTML files and other relevant items of websites. The researchers recommended that these websites ought to be designed supported further content; incorporate a lot of academic data, and priority ought to run for coming up with easy websites [4].

Table 3.1: Summary of the above literature review.

Title	Year	Short Description	Metrics Studies	Approach	Contribution	Shortcomings
Performance evaluation of websites using entropy and grey relational analysis methods: The case of airline companies	**2017**	This study have proposed a hybrid model to combine Grey Relational Analysis and Entropy Weight Method for determining and evaluating the performance of airline websites	Traffic, page rank, design optimization, load time, response time, markup and broken links	They used a combined both many rules decision-making methods were employed for the analysis of the performance about the airline websites by used that Entropy Weight and the Grey Relational Analysis.	They found endorsed that the performance and the performance metric were neglected by the airline's websites.	this study was for evaluating airline websites only and it's unless used for more domain and also researchers developed a static model to evaluate website performance.

An Empirical Performance Evaluation of Universities Website	2016	Present an empirical to evaluate universities website performance using automated Usability Testing tools like GTMETRIX, PINGDOM and results are analyzed based on said metrics in this paper.	Bandwidth, response time, page size and Performance,, load time, Speed, Mobile, SEO, Security, and No. of Requests	The focused methodology has been made to find all possible metrics in the website design with reference to some of the major Universities and four automated evaluation tool that is used to calculate the website performance.	Evaluated university websites in Jordan by automatic online evaluation tools for both performance and usability	This paper does not use all possible metrics in the website design.
Analytic Hierarchy Process (AHP) Based Model for Assessing Performance Quality of Library Websites	2016	Set up a scientific and implementable index system for the aim of analysis of web site performance quality that	Load time, number of components, page speed, page size,	They used AHP and FAHP proposes to measure and compare the	The model is used as a regular website design guideline that helps to develop usable	This study can adopt more fuzzy metrics to evaluate the website and this

		ought to lead the construction of the web site to an easy and informative level.	response time, mark-up validation, broken links, and design optimization	performance of those websites. This study engaged in an exceedingly scientific discussion on the feasibleness of the Analytical stratified method (AHP) approach supported a multi-metric decision-making methodology and real-world application to judge the performance of	websites across library domains.	study was for evaluating libraries websites only and it's unless used for more domain and also researchers developed a static model to evaluate website performance

				library websites.		
Framework for evaluation of academic website	**2016**	The main idea of this paper to create a website evaluation framework for academic websites.	Usability, Content, Presentation, Functionality, and Reliability	This paper design new evaluation framework based on the main quality factors of the selection and based on model (ISO 9126-1) and rearranged to set factors with an equivalent semantic meaning in one category by removing repetitions and different factor names.	This model is applied to evaluate the quality of websites using different quality assessment techniques starting in the earlier stages of the website design, during the intermediate develop stages and the deployment stages.	They used for analyzing qualitative data only without using more quantitative metrics.

Measuring Quality of Asian Airline Websites Using Analytical Hierarchy Process: A Future Customer Satisfaction Approach.	2013	The aim of this research is to evaluate the metrics which make a good quality website and to give a future approach to customer satisfaction with the websites. The high success factor for any online channel is the design of the website.	Load time page size, response time, page speed, availability, broken links, no. of component, response time, markup validation, design optimization, pagerank and traffic	Various web diagnostic online tools are used to evaluate each metric of the website. The data was taken in more than 30 trials at the different time to analyze the websites and used AHP Model from previous research to evaluate each metric	1. To propose a new methodology for evaluating the best airlines websites operates in Malaysia. 2. To explore the metric that constitutes a good quality website.	This study was for evaluating Asian airline's website only and it's unless used for more domain and also researchers developed a static model to evaluate website performance.
Empirical and Automated Analysis of Web Applications.	2012	This paper has set up that aesthetic factors are	Page load, response	This paper presented an	By this paper, they developed an	They used for analyzing

		decisive in deciding the quality of web application, and they surveyed various quality factors of web applications, and have empirically test web applications then they proposed an automatic tool, to calculate the quality and aesthetic factors of the web application.	time, optimal navigation times, HTML, maintainability, security, functionality, usability, efficiency, creditability and security	analysis methodology consistent with measurement approaches used in the performance evaluation domain and guideline review approaches used in the quality evaluation domain.	interacting tool to enable non-professional website builders to check for quality aspects	qualitative data only without using more quantitative metrics
A comparison of Asian e-government websites quality: using a non-parametric test	**2011**	The researchers suggested a method for selecting and evaluating the better e-government website based on some metrics of website	Load time, response time, page rank, the frequency of update,	They suggested some method for selecting and measuring the better e-government sites	This study confirmed that most Asian websites fail in performance and quality metrics by	This study was for evaluating most Asian websites only and it's unless used for more

		performance.	traffic, design optimization, page size, number of the item, accessibility error, markup validation, and broken link	based on multiple metrics of website performance, consisting of AHP, LWM , FAHP, and NHM.	applying the hybrid model approach.	domain and also researchers developed a static model to evaluate website performance.
Quality Ranking of E-Government Websites – PROMETHEE II Approach	**2011**	This study conducted to evaluate the e-government website performance about multiple Asian countries by web diagnostic tools.	Load time, response time, page rank, the frequency of update, traffic, design optimization, size, no of items,	They suggested a method for determining and measuring the better e-government websites by using several metrics of website performance.	selecting the best website between a group of e-government website.	This study was for evaluating e-government website only and it's unless used for more domain and also researchers developed a static model to

			accessibility error, markup validation, and broken link	They implemented the method by using both between of PROMETHEE II and AHP.		evaluate website performance.
Evaluation of Usage of University Websites in Bangladesh	**2011**	Two on-line automatic tools, i.e, HTML toolbox and web page analyzer were used beside a form directed towards users of those websites. Websites' internal options are known and suggestions are provided within the study to reinforce the usability of those websites. Several analysis ways are suggested to assess the	Total no of HTML files, HTML page sizes, composition, total number of images, and download time	Two online automatic tools, i.e, web page analyzer, and hypertext mark-up language toolbox were employed along with a questionnaire directed to users of these websites. Tools were applied to measure the websites' internal attributes which cannot be	This paper focuses both the user's purpose of view and automated tools to evaluate usability website.	This study can use more metrics to evaluate website.

		usability of internet sites to recommend enhancements within the style of internet sites.		understood by the users like HTML code errors, download time, and size of the HTML pages. The questionnaire was designed based on the 23 usability metric divided into five categories.		

3.2 Performance Standard

Every webpage design has its own features and these features have disadvantage and benefits. There is a mechanism for measuring the effects of the webpage component towards the performance and quality of the website. This mechanism measuring time and the size, component needed by the user in order to downloading a website. The main factors that will affect download time are page size (bytes), number and types of component, number of a server from the accessed web. Research makes by IBM may be used as a regular for measuring performance (Amerson et al., 2001) [33].

Table 3.2 describes all of the metric and performance standards that should be fulfilled by a website to be a good quality website. Tested metrics consist of: webpage loading time , average server response time, number of item per page and webpage size in bytes. Standard international download time in order to this performance can be used as a ref to categories the tested webpage. Automation in testing for website performance is a new opportunity and a new method, and should be applied for evaluating the performance of the website. For leveraging the effectiveness of continuous performance enhancement, the developer community has been aggressive in attaining TQM strategies by implementing ISO 9001:2000 kind (Sakthivel et al., 2007) [34].

Table 3.2: Standard of the website performance [33]

Evaluate Metric	Performance standard
Average server response time	< 0.5 second
Number of item per page	< 20 item
Webpage loading time	< 30 second
Webpage size in byte	< 64 Kbytes

Source: Amerson et al. (2001)

Broken links can give a bad effect for the truthfulness of a website. truthfulness is very important in the World Wide Web, because transaction between customer and seller is not on the spot and the risk of fraud is several times higher. The customer would truthfulness choose to buy from a website that looks professional.

3.3 Conclusions

In summary, the literature points out the fact that the importance of assessing performance in websites and identify several metrics along with which websites can be evaluated for performance and another approach can also be conducted for other service sectors such as e-business and academic websites [8]. And it is necessary to provide a method to evaluate the performance of websites by a dynamic model which includes various technological and logical factors. As a contribution to addressing this need, this study was aimed to build a dynamic model based on machine learning to evaluate websites performance. The model was developed on the premise of a conceptual framework, that consisted of quantitative quality metrics known.

Chapter 4

Proposed Method

This chapter proposes a new approach for evaluating the websites performance using machine learning. As shown in figure 4.1 and to implement this research. Thus, this chapter is split into six sections, in section 4.1 we will investigate the best metrics for measuring website performance, in section 4.2 we present the setup of the experiment that includes experimental environment, experimental tools, and experimental setting, in section 4.3 collection data for the metrics and creating of the dataset, in section 4.4 determining the regression methods to develop the model, in section 4.5 calculating weights for every metric. finally, in section 4.6 Models evaluation.

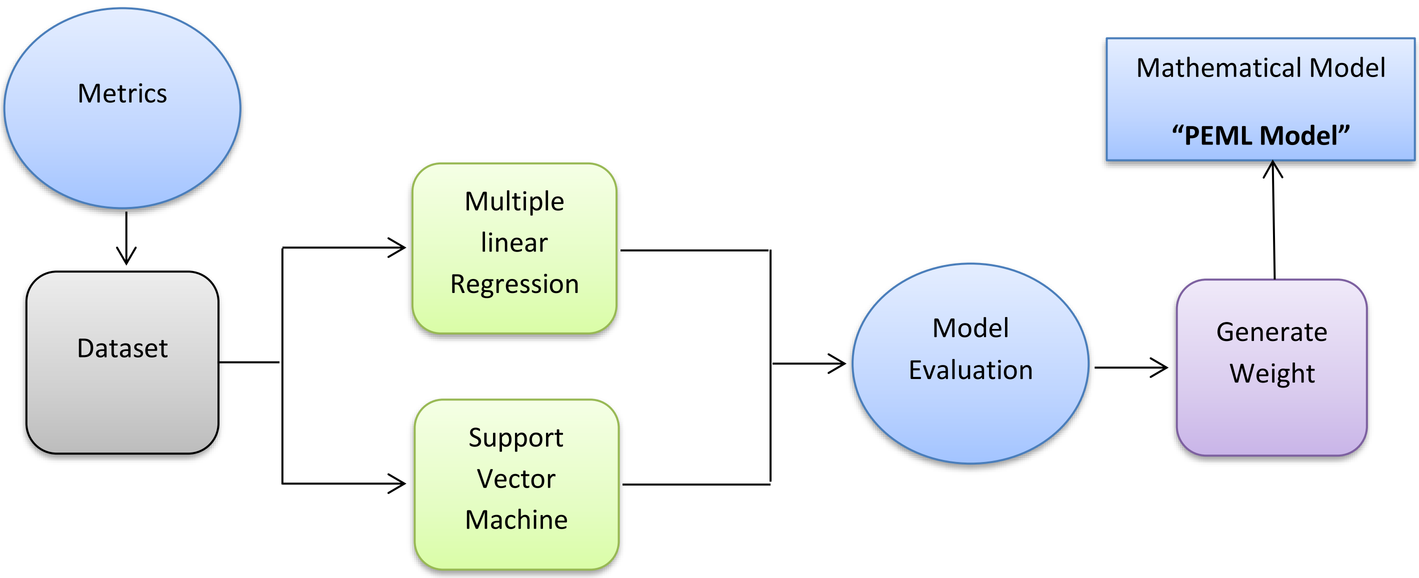


Figure 4.1: The steps of implement the methodology model

4.1 Identification of metrics that affect the performance of the website

There is a large number of metrics that affect websites performance; in our study, we have selected all metrics from the previous study and make Online Questionnaire to find out the local experts opinion for asking them "**What are the best metrics that affect websites performance?**". Thus, we take the metrics selected was good and excellent from the online questionnaire. Table 4.1 shows metrics were used in this study.

Table 4.1: Website Performance Evaluation Metrics by Online Questionnaire (experts opinion)

Choose the best metrics that affect website performance?	
Web Metric	**Poor / Good / Excellent**
Response Time	☐ Poor ☐ Good ☐ Excellent
Load Time	☐ Poor ☐ Good ☐ Excellent
Broken Links	☐ Poor ☐ Good ☐ Excellent
Bandwidth	☐ Poor ☐ Good ☐ Excellent
No. of Requests	☐ Poor ☐ Good ☐ Excellent
page size	☐ Poor ☐ Good ☐ Excellent
Number of items	☐ Poor ☐ Good ☐ Excellent
Page Speed	☐ Poor ☐ Good ☐ Excellent
Mark-up validation	☐ Poor ☐ Good ☐ Excellent
Throughput	☐ Poor ☐ Good ☐ Excellent
Design Optimization	☐ Poor ☐ Good ☐ Excellent
DNS Lookup Time	☐ Poor ☐ Good ☐ Excellent
Time To Interact	☐ Poor ☐ Good ☐ Excellent
Time To Title	☐ Poor ☐ Good ☐ Excellent
Time To Start Render	☐ Poor ☐ Good ☐ Excellent
Connection Time	☐ Poor ☐ Good ☐ Excellent
Time to First Byte	☐ Poor ☐ Good ☐ Excellent
Time to Last Byte	☐ Poor ☐ Good ☐ Excellent
Page Rank	☐ Poor ☐ Good ☐ Excellent

The Frequency of Update	☐ Poor ☐ Good ☐ Excellent
Accessibility Error	☐ Poor ☐ Good ☐ Excellent
Availability	☐ Poor ☐ Good ☐ Excellent
Optimal Navigation Times	☐ Poor ☐ Good ☐ Excellent
Total Number of Images	☐ Poor ☐ Good ☐ Excellent
Total Number of HTML Files	☐ Poor ☐ Good ☐ Excellent
Composition	☐ Poor ☐ Good ☐ Excellent

4.2 Experiments Setup

In this section, we have a description of the experimental environment of the experiments and determined the experimental tools that are used in the experiments, finally determine the setting of the experiments in the research.

4.2.1 Experimental Environment

We applied experiments on a machine with properties that is Intel (R) Core (TM) i5-4210U CPU @ 1.70 GHz (4CPU), 4.00 GB RAM, 500 GB hard disk drive and Windows 7, the 64-bit operating system installed.

4.2.2 Experimental Tools

In our experiments we used the following tools:

- **Snipping Tool:**

It is program to capture all or part of computer screen, and also can be add notes then save the snip from the tool window [13].

- **IBM SPSS Software:**

The IBM SPSS® software platform offers advanced applied math analysis, a massive library of machine-learning techniques, text analysis, open-source extensibility, integration with big data and seamless readying into applications. Its simple use, flexibility and measurability build IBM SPSS accessible to users with all expertise levels and outfits projects of all sizes and complexness to assist you and your organization to improve efficiency and minimize risk [14].

- **Microsoft Office Excel:**

We used to prepare and store dataset in tables, then do some simple preprocessing and analyze the results.

- **Rapid miner program:**

Is applied as an environment for machine learning and also used to data mining processes [19]. And also it is open-source and implemented in Java. It illustrates a new method to design even very complex problems - a modular operator concept which allows the design of intricate nested operator chains for a large variety of learning issues. RM uses XML to describe the operator trees modeling knowledge discovery (KD) processes. RM has elastic operators for data input and output in different file formats. It contents more than 100 learning schemes in order to classification, regression, and clustering tasks [12].

4.2.3 Experimental setting

In the research, table 4.2. Setting and configurations that are applied in the experiments.

Table 4.2: The environment of the experiment		
No	Experiment Issue	Notes
1	The internet browser	In this issue, we determine the Google Chrome browser of experiments
2	Internet speed	In our experiments we have 8 Mb/s internet speeds.

4.3 Collection of data and creating of the dataset

In the study, 26 metrics were identified for evaluating the performance of the website primarily. The number of metrics was reduced to 11 metrics by 4 experts. The experts were computer engineers and experienced in software, web design, web masters; as shown in Table 4.3 the metrics were used in this study and their descriptions.

Table 4.3: Website Performance Measurement Metric	
Web Metric	**Description**
Response Time	A website server should respond to a browser request within certain metrics.
Load Time	It is used to calculate the time required to load a page and its graphics.
Broken Links	Broken links always reduce the quality of the website. Websites have internal or external links. A visitor expects the links to be valid, loads successfully to the clicked page.
No. of Request	The number of request/response between a client and a host.
page Size	The size of the web pages in the website.
mark-up validation	It is utilized to assess and calculate the number of HTML errors, which exist on the website, such as orphan codes, coding errors, missing tags and etc.

design optimization	The scripts, HTML or CSS codes optimized for faster loading. The optimization also reduces the number of website elements such as images, scripts, html, css codes or video.
Page Speed	Page speed is often confused with "site speed," which is actually the page speed for a sample of page views on a site. Page speed can be described in either "page load time" (the time it takes to fully display the content on a specific page) or "time to first byte" (how long it takes for your browser to receive the first byte of information from the web server).
Start time render	is measured as the time from the start of the initial navigation until the first non-white content is painted to the browser display.
Connection time	is time that the web browser is connecting to the server.
DNS lookup	DNS time is the amount of time it takes a domain lookup to occur while browser retrieves a resource.

Using website diagnostic tools for collecting data for all metrics, and creating the dataset will take place. All of the data for this research was taken using PC with specification: Intel(R) Core(TM) i5-4210 CPU @ 1.70GHz, using Local Area Network internet connection with 8 Mb/s internet speeds; Table 4.4. Website diagnostic tools.

We used a number of widely available web diagnostic tools online, thus we used widely available website performance tool and webpage speed analyzer online service (www.gtmetrix.com). List of performance measured and reported by this service include page size, number of request (HTML, images, CSS, scripts), and load time. Another available online tool that we used which is for testing quality was: (www.duplichecker.com/broken-link-checker.php) which was utilized in order to monitor broken links as a dead link on the website. Another available online tool (www.websitepulse.com) that we used which is for Verifies the server status, downloads the full HTML content, measures the response time of the tested website and also the time needed for the DNS and connection time to the server. Also available online tool (https://www.1and1.com/website-checker) that used to check the number of website elements such as images, scripts, html, css codes or video. The W3C's HTML validator website (http://validator.w3.org) was used to validate the HTML code of web documents. There is also tool (http://www.webpagetest.org) that we used to check the time from the start of the initial navigation until the first non-white content is painted to the browser display.

Table 4.4: Online Web- Diagnostic Tools for Data Collection

Web Metric	Web- Diagnostic Tools	Measurement unit
Response Time	www.websitepulse.com	Second
Load Time	www.gtmetrix.com	Second
Broken Links	www.duplichecker.com/broken-link-checker.php	Number
No. of Requests	www.gtmetrix.com	Number
page size	www.gtmetrix.com	Number
page speed	www.gtmetrix.com	Number
mark-up validation	https://validator.w3.org/#validate_by_url	Number
design optimization	https://www.1and1.com/website-checker	%

Connection Time	https://www.websitepulse.com/	Second
Start Time Render	https://www.webpagetest.org/	Second
DNS Lookup	https://www.websitepulse.com/	Second

As shown in table 4.5, we collected data for 174 random websites in different domains, such as : (Education, health, government, and business).

		Second	Second	Number	MB	Number	%	Number	Number			
Domain		Response Tir	Load Time	roken Link	Page Size	-up valid	n optimiz	of Reque	tart Rende	Ns Look	unection T	erformance
https://www.alquds.edu/ar/	1	1.955	6.8	2	1.48	53	67	75	3.7	0.146	0.146	75
https://www.najah.edu/ar/	2	1.641	2.69	0	3.97	30	75	70	2.7	0.008	0.001	70
http://www.qou.edu	3	1.847	24.9	0	4.43	5	66	86	1.8	0.084	0.001	77
https://www.alaqsa.edu.ps/ar/hom	4	3.869	10.4	2	1.98	42	55	85	5.4	0.148	0.162	65
http://www.hebron.edu/index.php/a	5	9.058	12.7	113	1.4	73	20	93	9.9	0.402	0.146	73
https://cu.edu.eg/ar/Home	6	6.516	7	3	1.43	97	58	91	4.8	0	0.154	74
https://www.bethlehem.edu/arabic	7	0.27	3.7	0	1.83	44	64	64	2.3	0	0.013	71
http://www.damascusuniversity.edu	8	3.873	24.2	13	0.861	477	30	54	8	0.201	0.184	80
http://paluniv.edu.ps/	9	7.758	19.4	12	4.19	55	46	111	9.5	4.138	0.149	65
https://www.birzeit.edu/ar	10	0.288	5.7	1	4.9	55	58	89	2.3	0	0.141	77
http://uobaghdad.edu.iq/	11	4.418	10.3	2	6.87	95	67	72	3.3	2.129	0.001	80
http://nahrainuniv.edu.iq/ar	12	3.282	3.5	6	3.52	52	41	111	1.4	0	0	71
http://www.alazhar.edu.ps/arabic/i	13	4.643	8.8	2	8.81	40	61	192	2.8	3.744	0.143	63
http://www.kuniv.edu/ku/ar/	14	4.643	11.4	1	6.95	2	53	61	7.1	3.744	0.143	65
https://www.ut.edu.lb/	15	3.175	12.3	2	19	18	61	299	6.7	1.052	0.096	66
http://www.helwan.edu.eg/Arabic/	16	5.678	8.5	32	2.51	54	30	74	20.4	0.362	0.135	69
http://www.miuegypt.edu.eg/	17	6.235	4.1	9	3.69	139	57	130	4.5	0.184	0.074	67
http://futureuniversity.com/	18	2.178	3.9	3	1.08	24	62	60	19.8	0.075	0.07	75
http://alexu.edu.eg/index.php/ar/	19	6.015	10.6	1	18.8	58	46	95	4.5	0.231	0.138	75
http://www.bau.edu.lb/	20	1.749	13.5	1	7.55	46	64	132	3.7	1.095	0.083	75
http://www.ju.edu.jo/ar/arabic/hon	21	1.493	16.9	10	7.13	52	52	170	21.4	0	0.153	75
https://www.yu.edu.jo/	22	2.638	7.1	7	1.4	115	64	68	5.7	0.232	0.154	66
https://hu.edu.jo/	23	2.382	4.4	0	1.26	12	71	72	2.2	1.249	0.153	66
http://www.ahu.edu.jo/	24	0.722	8.4	0	9.05	12	51	101	3.7	0.257	0.155	67
https://www.ul.edu.lb/default.aspx	25	6.199	7.5	2	332	10	55	30	6.3	0.285	0.153	79
http://www.aun.edu.eg/arabic/	26	2.886	17	0	6.08	1001	63	119	2.3	1.193	0.163	78

Table 4.5: Sample of the original dataset

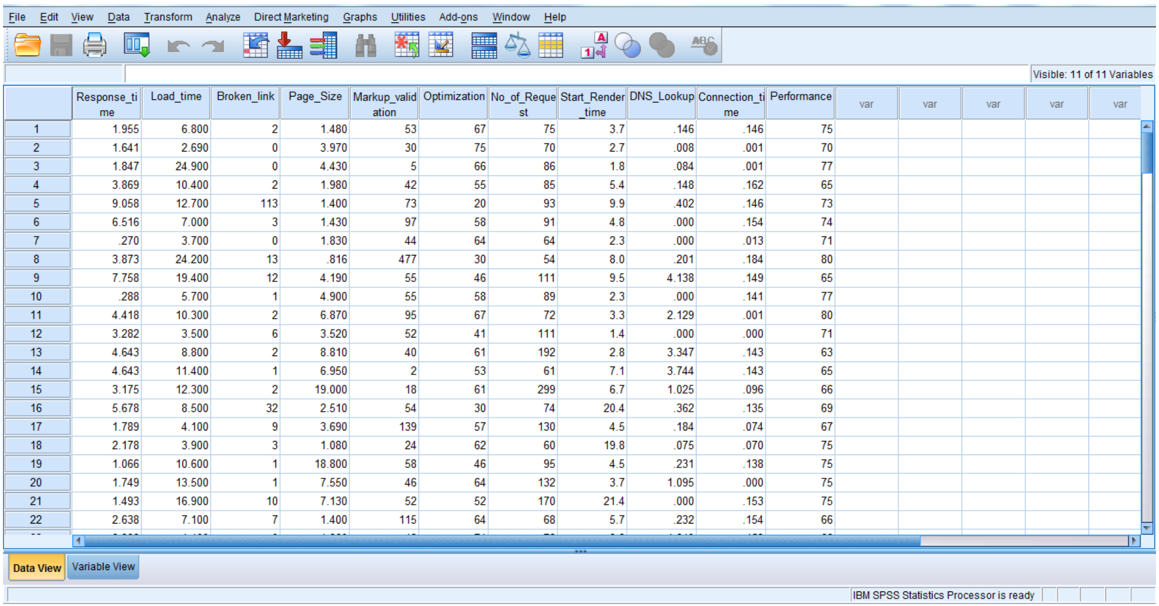
As shown in table 4.6 the dataset considered for analysis and along with a description of the dataset is as shown in table 4.7.

Response	Load_time	Broken_li	Page_Size	Markup_v	Optimizat	No_of_Re	Start_Ren	DNS_Look	Connectic	Performan
1.955	6.8	2	1.48	53	67	75	3.7	0.146	0.146	75
1.641	2.69	0	3.97	30	75	70	2.7	0.008	0.001	70
1.847	24.9	0	4.43	5	66	86	1.8	0.084	0.001	77
3.869	10.4	2	1.98	42	55	85	5.4	0.148	0.162	65
9.058	12.7	113	1.4	73	20	93	9.9	0.402	0.146	73
6.516	7	3	1.43	97	58	91	4.8	0	0.154	74
0.27	3.7	0	1.83	44	64	64	2.3	0	0.013	71
3.873	24.2	13	0.861	477	30	54	8	0.201	0.184	80
7.758	19.4	12	4.19	55	46	111	9.5	4.138	0.149	65
0.288	5.7	1	4.9	55	58	89	2.3	0	0.141	77
4.418	10.3	2	6.87	95	67	72	3.3	2.129	0.001	80
3.282	3.5	6	3.52	52	41	111	1.4	0	0	71
4.643	8.8	2	8.81	40	61	192	2.8	3.744	0.143	63
4.643	11.4	1	6.95	2	53	61	7.1	3.744	0.143	65
3.175	12.3	2	19	18	61	299	6.7	1.052	0.096	66
5.678	8.5	32	2.51	54	30	74	20.4	0.362	0.135	69
6.235	4.1	9	3.69	139	57	130	4.5	0.184	0.074	67
2.178	3.9	3	1.08	24	62	60	19.8	0.075	0.07	75
6.015	10.6	1	18.8	58	46	95	4.5	0.231	0.138	75
1.749	13.5	1	7.55	46	64	132	3.7	1.095	0.083	75
1.493	16.9	10	7.13	52	52	170	21.4	0	0.153	75
2.638	7.1	7	1.4	115	64	68	5.7	0.232	0.154	66
2.382	4.4	0	1.26	12	71	72	2.2	1.249	0.153	66
0.722	8.4	0	9.05	12	51	101	3.7	0.257	0.155	67

Table 4.6: The dataset for analysis

Table 4.7: description of the dataset	
Metric	**Type**
Response Time	Numeric value
Load Time	Numeric value
Broken Links	Numeric value
No. of Requests	Numeric value
page size	Numeric value
page speed	Numeric value
mark-up validation	Numeric value
design optimization	Numeric value
Start time render	Numeric value
Connection time	Numeric value
DNS lookup	Numeric value

After that, SPSS statistical tool to find the most influence metric to enhancing the website performance among all the collected metrics and rule out every metric unless has no affect website performance (see figure 4.2).



	Response_time	Load_time	Broken_link	Page_Size	Markup_validation	Optimization	No_of_Request	Start_Render_time	DNS_Lookup	Connection_time	Performance	var	var	var	var	var
1	1.955	6.800	2	1.480	53	67	75	3.7	.146	.146	75					
2	1.641	2.690	0	3.970	30	75	70	2.7	.008	.001	70					
3	1.847	24.900	0	4.430	5	66	86	1.8	.084	.001	77					
4	3.869	10.400	2	1.980	42	55	85	5.4	.148	.162	65					
5	9.058	12.700	113	1.400	73	20	93	9.9	.402	.146	73					
6	6.516	7.000	3	1.430	97	58	91	4.8	.000	.154	74					
7	.270	3.700	0	1.830	44	64	64	2.3	.000	.013	71					
8	3.873	24.200	13	.816	477	30	54	8.0	.201	.184	80					
9	7.758	19.400	12	4.190	55	46	111	9.5	4.138	.149	65					
10	.288	5.700	1	4.900	55	58	89	2.3	.000	.141	77					
11	4.418	10.300	2	6.870	95	67	72	3.3	2.129	.001	80					
12	3.282	3.500	6	3.520	52	41	111	1.4	.000	.000	71					
13	4.643	8.800	2	8.810	40	61	192	2.8	3.347	.143	63					
14	4.643	11.400	1	6.950	2	53	61	7.1	3.744	.143	65					
15	3.175	12.300	2	19.000	18	61	299	6.7	1.025	.096	66					
16	5.678	8.500	32	2.510	54	30	74	20.4	.362	.135	69					
17	1.789	4.100	9	3.690	139	57	130	4.5	.184	.074	67					
18	2.178	3.900	3	1.080	24	62	60	19.8	.075	.070	75					
19	1.066	10.600	1	18.800	58	46	95	4.5	.231	.138	75					
20	1.749	13.500	1	7.550	46	64	132	3.7	1.095	.000	75					
21	1.493	16.900	10	7.130	52	52	170	21.4	.000	.153	75					
22	2.638	7.100	7	1.400	115	64	68	5.7	.232	.154	66					

Figure 4.2: The most influence among the collected metrics

4.4 Determine machine learning method

Machine learning methods are the backbone of our approach in the research where used to generate the weight of the metric. Hence, the task of regression and classification is to predict website performance (y) based on metrics (X), based on the dataset :

If Y is numerical, the task is called **regression**.

If Y is nominal, the task is called **classification**.[17]

There are various algorithms for regression methods. Hence, we applied linear regression and support vector machine regression that depends on the volume and structure of the dataset. In this thesis, we have two different algorithms for conducting the experiments on the same dataset, namely, linear regression and support vector machine to explains the comparison of the models that give the best results in terms of the Correlation coefficient in the performance evaluation metric.

4.4.1 linear regression model

the technique is a statistical approach to construct a linear model predicting the value of the metric while knowing the values of the other metrics. It employs the least mean square method in order to adjust the parameters of the linear model/function [12]. The main process of linear regression method that we applied on the experiment; this method is implemented via Rapid Miner tools (see figure 4.3):

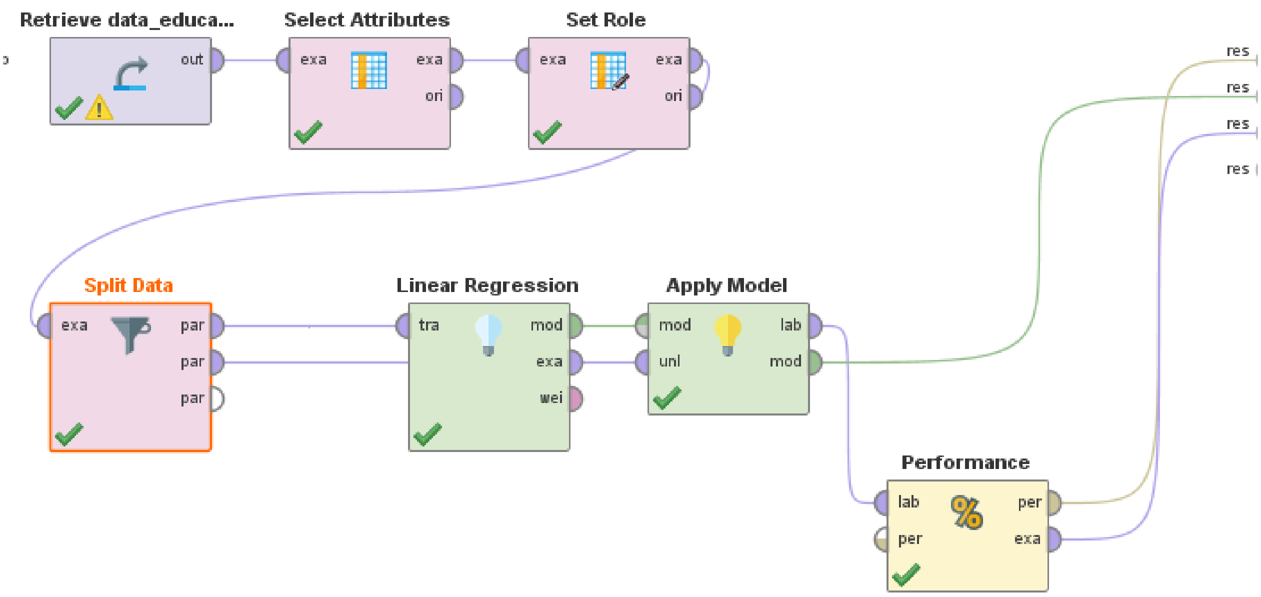


Figure 4.3: The main process of linear regression method in Rapid Miner tool

The previews figure 4.3 —the main process of the linear regression method includes the following steps:

1. **Retrieve**: a dataset is loaded to the process using *Read Excel* operator.
2. **Select Attributes:** this Operator selects a subset of metrics of an set and removes the other metrics, in our case we selected all metrics.

3. **Select Role:** The role of a metric describes how other operators handle this metric. We selected role is the label, which the metrics with the label role acts as a target metric for learning operators.
4. **Split Data:** this operator is a particular operator adapted to divide the dataset to the training and the testing datasets. In our case we make a split 80:20, in particular, starting from the dataset are created the training dataset and the testing dataset containing respectively 80% and 20% of the data, respectively. The testing dataset is used to test the accuracy of the created model.
5. **Modeling**: a dataset is fed into a linear regression operator, which is responsible for building and calculating the linear regression model and to get a prediction on unseen data.
6. **Evaluation**: to apply a linear regression model on the dataset and to predict the performance, the Apply model operator is used. On the other hand, the performance of the linear regression model in prediction is evaluated and verified using %Performance (Regression) operator. The %Performance (Regression) operator is customized to measure the performance of regression models only. Therefore, the selection of the evaluation metrics; Correlation Coefficient (CC), average absolute error, and average relative error is made in this stage.

4.4.2 Support vector machine regression model

The algorithm builds support vectors in a high-dimensional feature area. Then, hyperplane with the maximal margin is constructed. The kernel function is used to transform the data, whose augments the dimensionality of the data. This augmentation stimulates that the data can be separated with a hyperplane with much higher probability, and establish a minimal prediction probability error measure [12]. The main process of support vector machine method that we applied on the experiment; this method is implemented via RapidMiner tools (see figure 4.4):

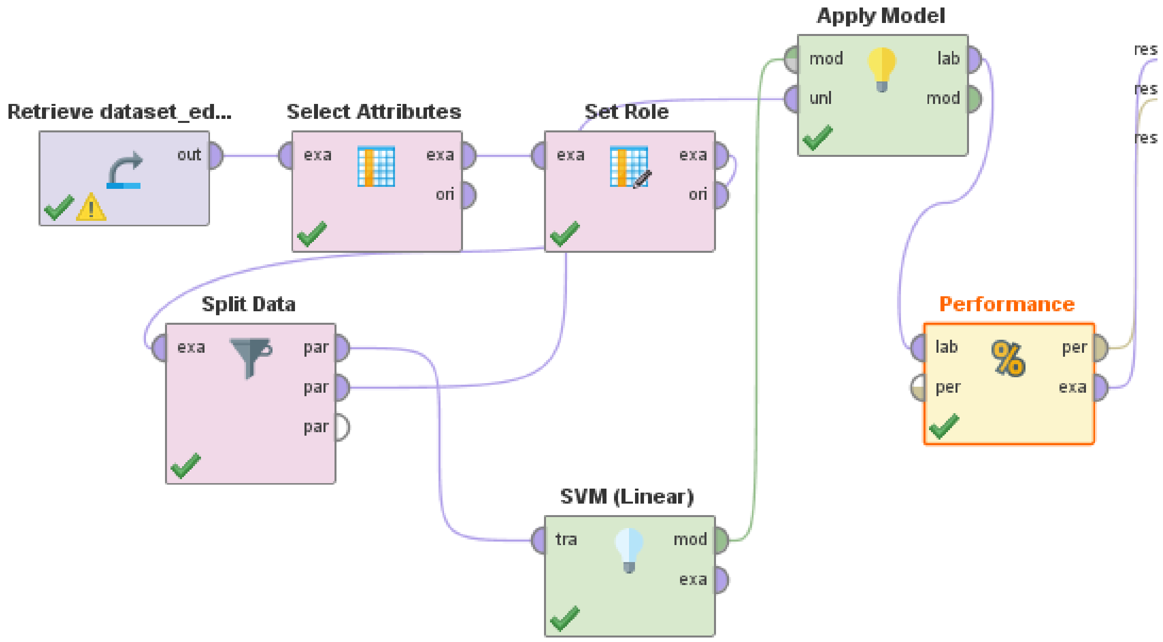


Figure 4.4: The main process of support vector machine method in RapidMiner tool

The previews figure 4.4 —the main process of support vector machine method includes the following steps:

1. **Retrieve**: a dataset is loaded to the process using *Read Excel* operator.

2. **Select Attributes:** this Operator selects a subset of metrics of an set and removes the other metrics, in our case we selected all metrics.

3. **Select Role:** The role of a metric describes how other operators handle this metric. We selected role is the label, which the metrics with the label role acts as a target metric for learning operators.

4. **Split Data:** this operator is a particular operator adapted to split the dataset into the training and the testing datasets. In our case we make a split 80:20, in particular,

starting from the dataset are created the training dataset and the testing dataset containing respectively 80% and 20% of the data, respectively. The testing dataset is used to test the accuracy of the created model.

5. **Modeling**: a dataset is fed into support vector machine regression operator, which is responsible for building and calculating the support vector machine model and to get a prediction on unseen data.
6. **Evaluation**: to apply the support vector machine model on the dataset and to predict the performance, the apply model operator is used. On the other hand, the performance of the support vector machine model in prediction is evaluated and verified using %Performance (Regression) operator. The %Performance (Regression) operator is customized to measure the performance of regression models only. Therefore, the selection of the evaluation metrics; Correlation Coefficient (CC), average absolute error, and average relative error is made in this stage.

4.5 Calculating weights for every metric

In this step, we generated a weight for every metric by using regression methods. Moreover, after generated weight to every metric, we can arrange the most affect metrics on the website's performance on the level of the hierarchy as shown in figure 4.5.

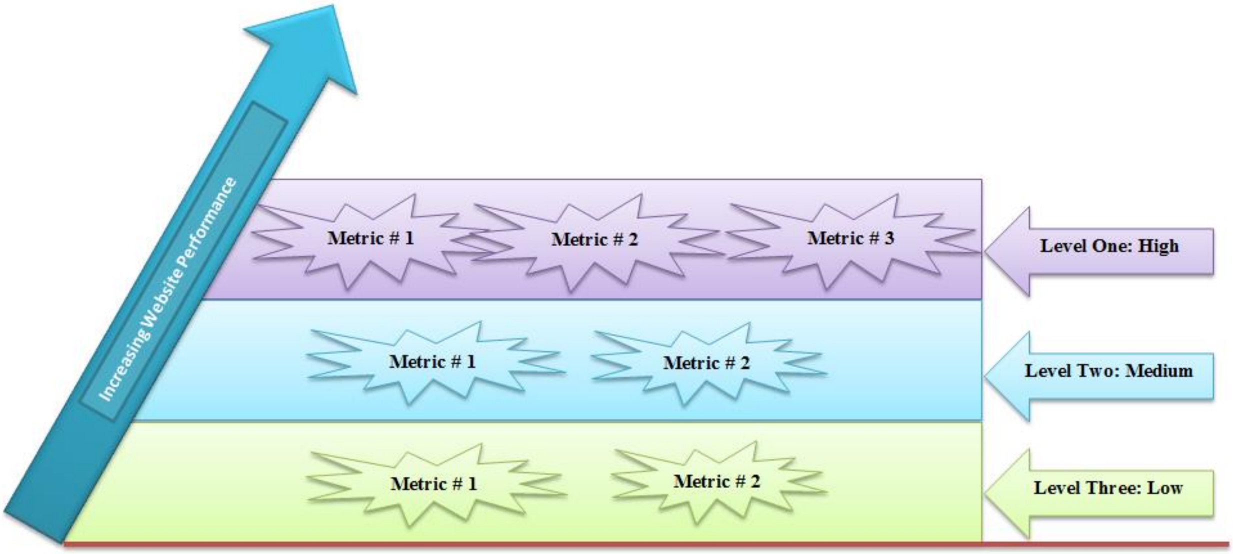


Figure 4.5: The level of the hierarchy of web metrics

4.6 Model evaluation

The weights of metrics were calculated by using the regression Methods and then evaluate the performance of the websites using mathematical model. Hence, After building different regression models namely, linear regression model and support vector machine regression model. There are criteria whereby they can be evaluated and compared to take the best performance among the models.

- **Average absolute error:** it represents the average absolute deviation of the prediction from the actual value (it is expressed in website performance)[11].

- **Average relative error:** it is calculated as the average of the prediction that sees in the numerator the error in absolute value among the predicted values and the respective real values and the denominator the real value (it is expressed in percentage) [11].

- **Correlation:** it provides a percentage correlation value among predicted and actual values in a range between 0 and 100 where 100 represents the perfect forecast of data by the model (it is expressed in percentage) [11].

Chapter 5

Model Analysis and Evaluation

In this chapter, we present the results of research experiments that presented in the previous chapter and finally we discuss these results. The results include four sections, in section 5.1 we present model analysis by using two different algorithms by linear regressions and support vector machine regression, in section 5.2 we present evaluation of the models to adopt the best performance for models, in section 5.3 Identifying most affect metrics in the level of the hierarchy, in section 5.4 we present modeling details, and in section 5.5 we present the results of the proposed model compared to other methods in the previous studies.

5.1 Model Analysis

In this section are discussed experimental analysis by using SPSS tools and RapidMiner, in order to get most affected metrics and to take the best algorithm performance.

5.1.1 Model Analysis Using SPSS Tool

In order to determine the most influential metric on the performance of websites from the dataset collected, as mentioned in section 4.3, we run SPSS on the same dataset. Thus, The number of metrics was reduced to 7 metrics were the most affect website performance based on significant in coefficient table. Table 5.1 the coefficient table after performing the statistical analysis into the SPSS tool.

Table 5.1: Coefficients of used metrics

Coefficients[a]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	79.006	1.965		40.201	.000
Broken_link	-.109	.014	-.445	-7.555	.002
page_size	-.419	.121	-.194	-3.464	.001
response_time	-.563	.318	-.099	-1.769	.048
No_of_Request	-.056	.016	-.209	-3.545	.001
Optimization	.054	.022	.132	2.398	.018
load_time	-.175	.075	-.130	-2.319	.022
Markup_validation	-.012	.006	-.104	-2.022	.045

Result of above coefficient table:

Multiple regression were run to predict performance from metrics. These metrics statistically significantly predicted performance, $p < .05$. Hence, we retain to those metrics whose significant level is < 0.05 and remove those metrics whose significance level is > 0.05 from the model. Table 5.2 the metrics that have significantly impact the performance of websites after SPSS analysis from the dataset.

Table 5.2: Highly affected metrics on website performance

Metrics	Type
Response Time	Numeric value
Load Time	Numeric value
Broken Links	Numeric value
No. of Requests	Numeric value
page size	Numeric value
mark-up validation	Numeric value
design optimization	Numeric value

5.1.2 Model Analysis Using Machine Learning

After determining the metrics that significantly impact the performance of websites from the dataset as mentioned in section 5.1.1. Therefore, we have used various regression methods namely linear regression and support vector machine regression on the same dataset as mentioned in section 4.4. The experiments aimed to compare machine learning algorithms to take the best algorithm to create a model for the evaluation of the website performance.

5.1.2.1 Linear Regression Results and Analysis

In order to evaluate the performance of the linear regression model by using Rapidminer tool, we run an experiment on the dataset. As Shown in figure 5.1 to understand how the prediction is successful, correlation, average absolute error, and average relative error as mentioned in section 4.4.1.

PerformanceVector

```
PerformanceVector:
absolute_error: 5.897 +/- 4.624
relative_error: 9.64% +/- 7.66%
correlation: 0.715
```

Figure 5.1: Performance of model by LR

Figure 5.2 the plot of prediction of performance of the websites versus the linear line using the linear regression method, The straight line in red represents the real values of the performance of websites, and the blue line indicates the deviation in the prediction of linear regression.

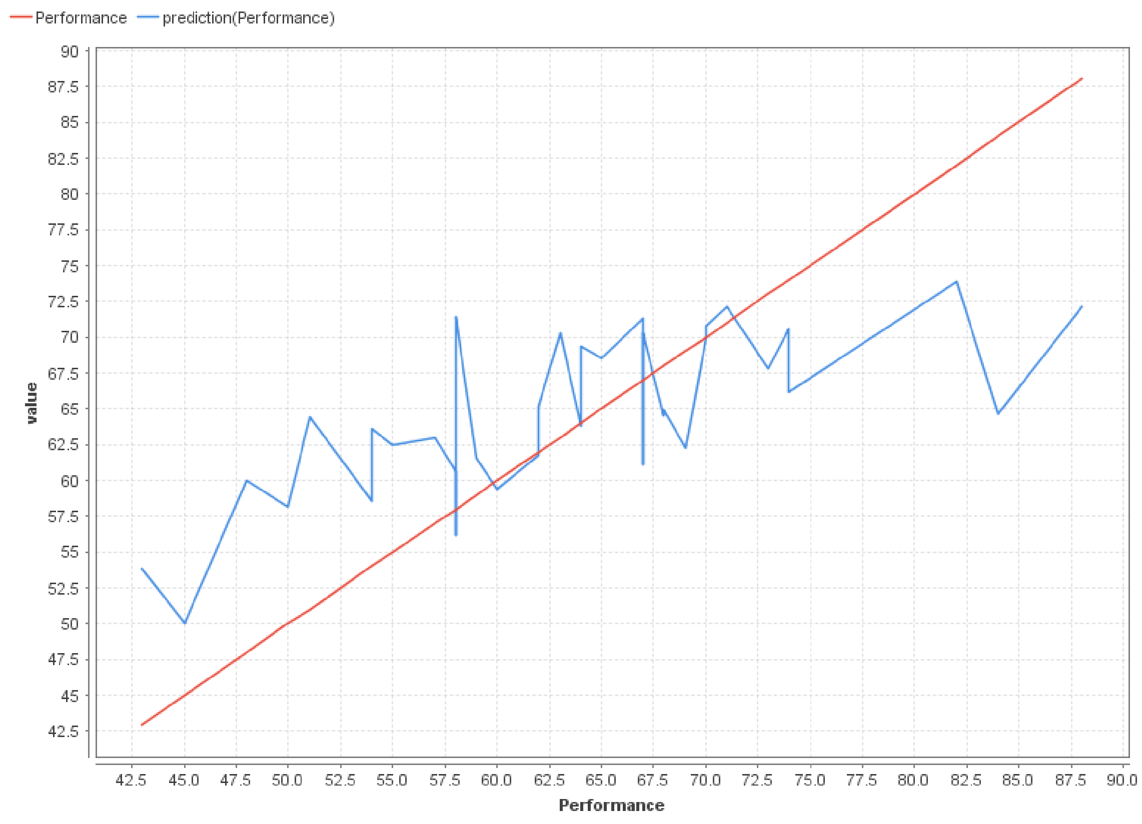


Figure 5.2 The plot of prediction of performance of the websites versus the linear line using the linear regression method

5.1.2.2 Support Vector Machine Results and Analysis

In order to evaluate the performance of the support vector machine model by using Rapidminer tool, we run an experiment on the same dataset. As Shown in figure 5.3 to understand how the prediction is successful, correlation, average absolute error, and average relative error as mentioned in section 4.4.2.

PerformanceVector

```
PerformanceVector:
absolute_error: 6.993 +/- 5.277
relative_error: 11.72% +/- 9.75%
correlation: 0.652
```

Figure 5.3: Performance of model by SVM

5.2 Model Evaluation

The experiments aimed to compare machine learning algorithms to create a model for the evaluation of the website's performance. In order to evaluate the performance of our model. We take the best algorithm based on correlation, average absolute error, and average relative error as mentioned in section 4.6.

Our approach aims to achieve the best performance results in comparison to the state between the two models. We evaluated our approach on the same dataset. Table 5.3 the comparison results of Models. The correlation in linear regression model shows a good prediction is 71.5 % compared with the correlation support vector machine 65.2%. However, the linear regression provides the best result with the minimal average absolute error is 5.897 +/- 4.624 and the minimal average relative error 9.64% +/- 7.66% with the other model.

Table 5.3: Results comparison results of models

Model	Correlation (Min/Max %)	Average Absolute Error	Average Relative Error	Time To Build Model
Multiple linear Regression	71.5 %	5.897 +/- 4.624	9.64% +/- 7.66%	1 Sec
Support Vector Machine	65.2 %	6.993 +/- 5.277	11.72% +/- 9.75%	3 Sec

In this research, we have used measurement metrics namely: correlation, average absolute error, and average relative error. After the analysis, we concluded that the different between linear regression and support vector machine is that the linear regression model gives the best performance result and it has the lowest error rate. It also takes less time to build the model. Hence, we concluded that linear regression gives the highest accurate model to generate weights for metrics.

Figure 5.4 and Figure 5.5 some output results concerning the comparison with real websites performance data and predictive ones using linear regression and support vector machine according to the cases of Table 5.3. The results must be read as follow:

If the prediction is similar to the real data concerning website performance will follow the same trend, otherwise will occur a trend variation.

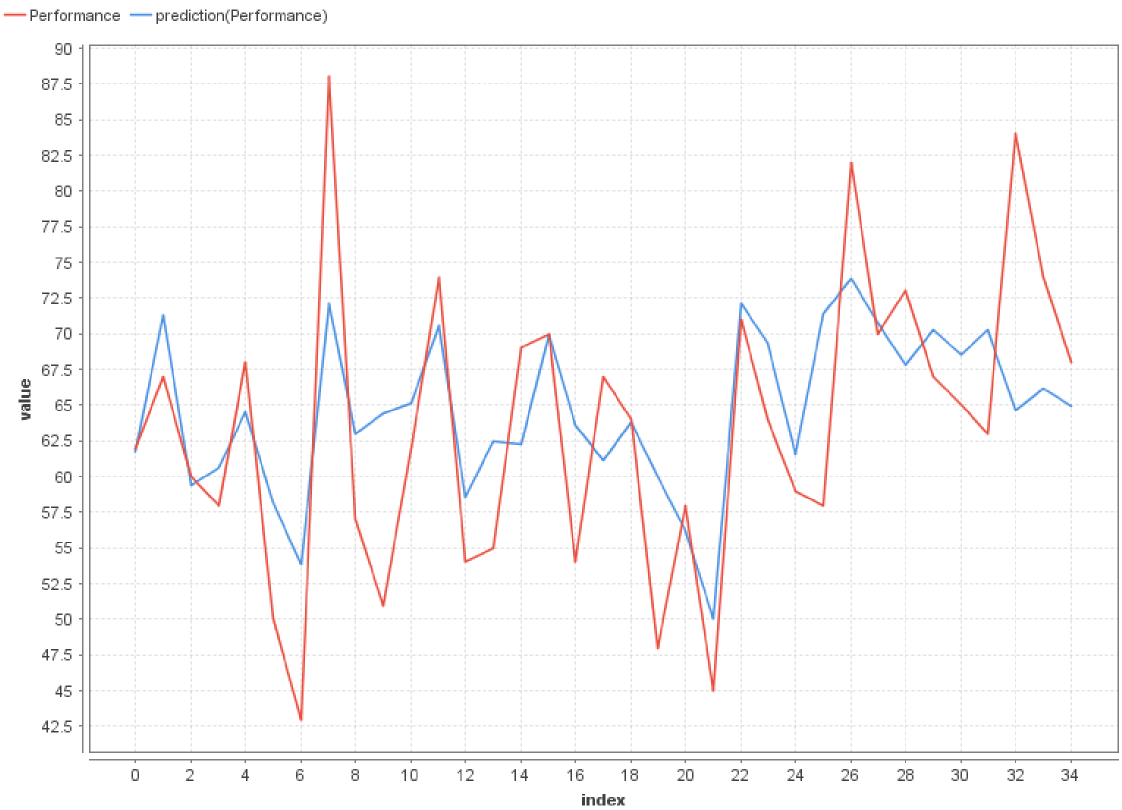


Figure 5.4: Comparison with real websites performance data and predictive ones by linear regression model

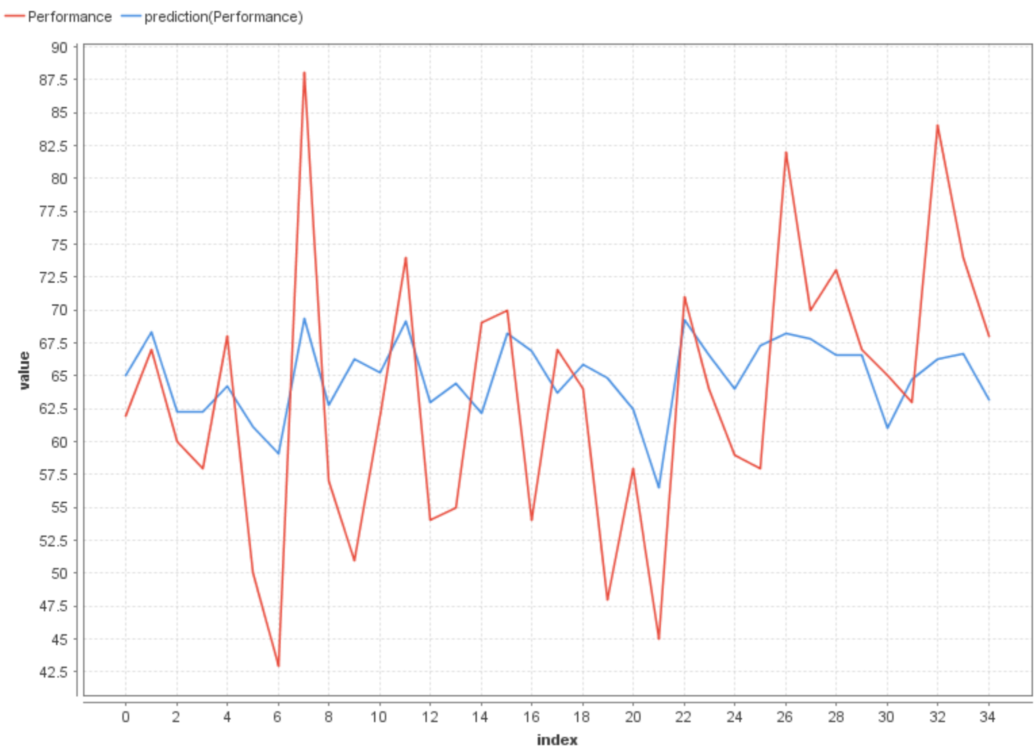


Figure 5.5: Comparison with real websites performance data and predictive ones by Support Vector Machine model

Result of below correlations matrix:

Figure 5.6 describe the correlation between all metrics and it can produce a weights vector based on these correlations. And also correlation is a statistical mechanism in order to can show whether and how strongly pairs of metrics are related.

Attributes	Response_time	Load_time	Broken_link	Page_Size	Markup_validation	Optimization	No_of_Request	Performance
Response_time	1	0.283	0.158	-0.005	0.111	-0.315	0.145	-0.289
Load_time	0.283	1	0.294	0.293	0.095	-0.124	0.133	-0.400
Broken_link	0.158	0.294	1	0.351	-0.016	0.029	0.422	-0.650
Page_Size	-0.005	0.293	0.351	1	-0.017	0.064	0.288	-0.438
Markup_validation	0.111	0.095	-0.016	-0.017	1	-0.098	0.117	-0.154
Optimization	-0.315	-0.124	0.029	0.064	-0.098	1	0.210	0.121
No_of_Request	0.145	0.133	0.422	0.288	0.117	0.210	1	-0.469
Performance	-0.289	-0.400	-0.650	-0.438	-0.154	0.121	-0.469	1

Figure 5.6: The correlation matrix among metrics

A correlation is a number between -1 and +1 that measures the degree of association between two metrics (call them X and Y). A positive value for the correlation implies a positive association like the association between website performance and design optimization, where the optimal design can lead to the best website performance. And also a negative value for the correlation implies a negative or inverse association like the association between website performance and response time, where any decrease in response time can result to the best performance.

5.3 Identifying most important metrics

Figure 5.7 show calculate the relevance of the metrics by computing the value of correlation for each metric with respect to website performance as mentioned in the section 4.5. Thus, we arranged the metrics from a high correlation to low correlation based on the weight to every metric.

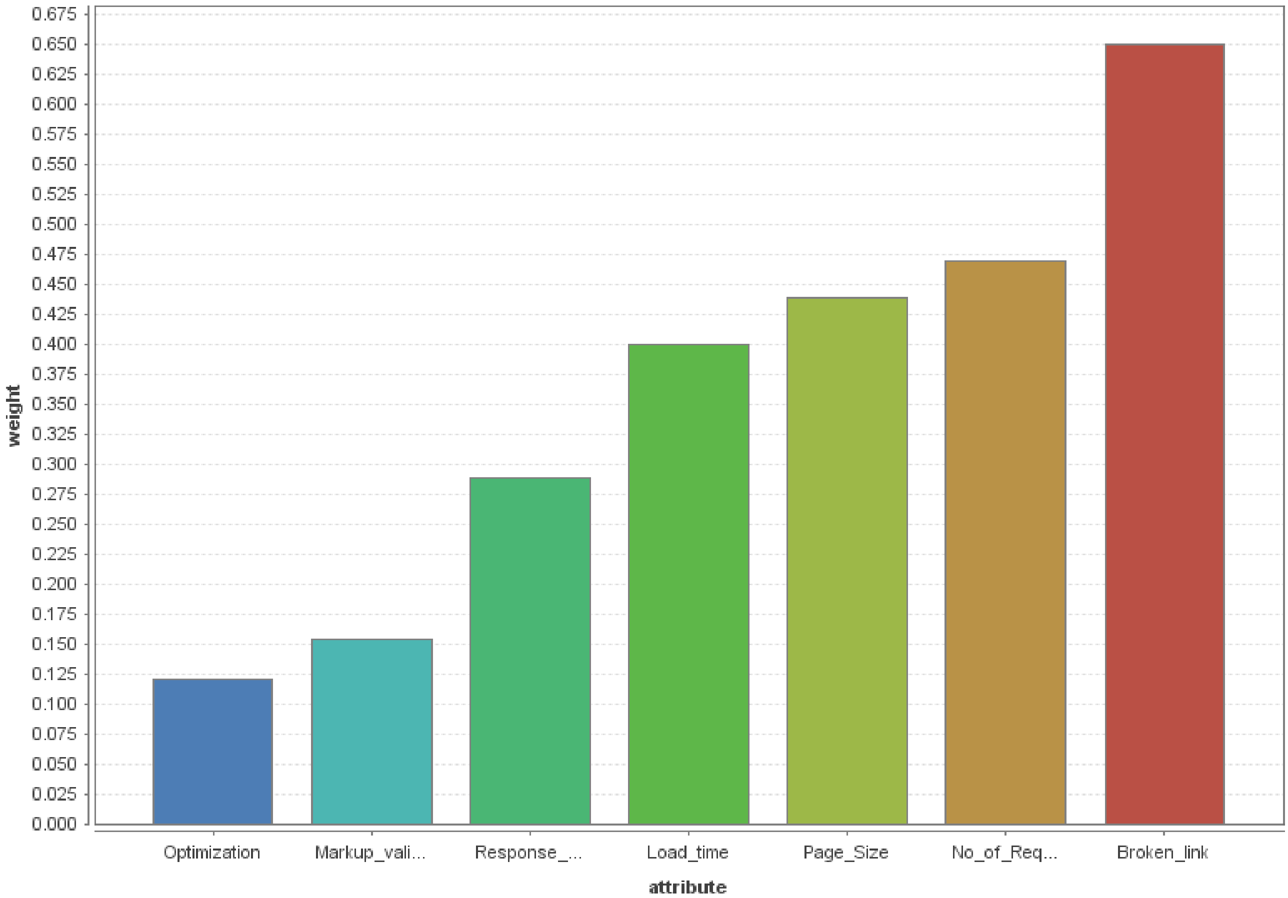


Figure 5.7 Correlation the relevance of the metric

Therefore, Figure 5.8 arranged metrics in the level of the hierarchy help webmasters and decision-makers to know what improvements are needed to enhance the performance as shown in figure 5.7 above.

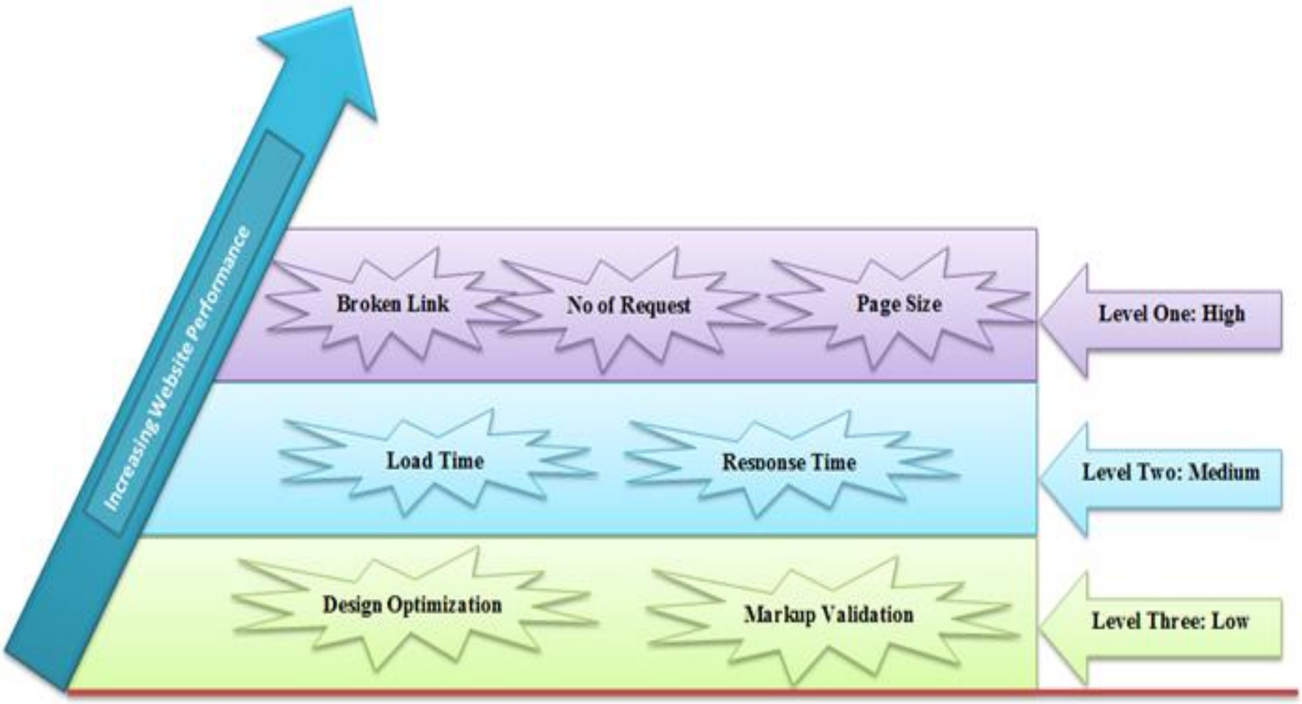


Figure 5.8: The level of the hierarchy of web metrics

5.4 Building Model

After determining the best performance between the two models as mentioned in section 5.2. we developed a new dynamic model to evaluate websites performance based on the proposed mathematical model that we called is PEML. Figure 5.9 the linear regression model using machine learning.

LinearRegression

```
- 0.596 * Response_time
- 0.154 * Load_time
- 0.105 * Broken_link
- 0.415 * Page_Size
- 0.013 * Markup_validation
+ 0.070 * Optimization
- 0.051 * No_of_Request
+ 77.610
```

Figure 5.9: The linear regression model

Finally, we extracted equation that used to evaluate websites performance by using the best performance among models. Figure 5.10 the express formula model :

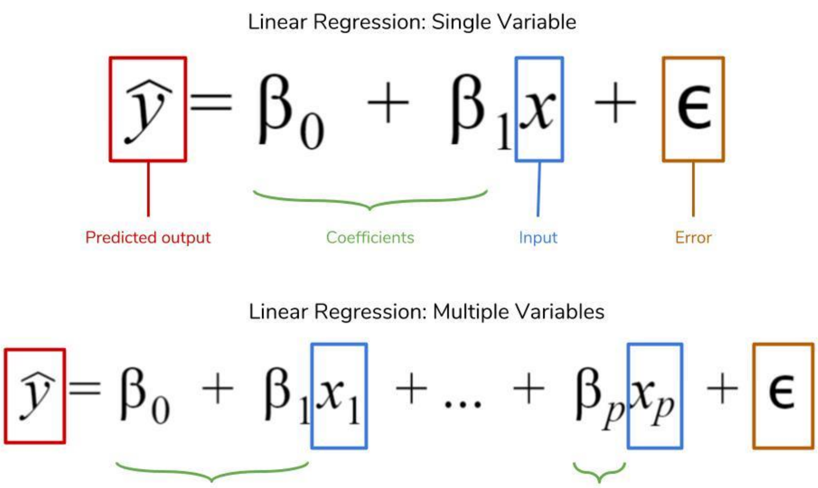


Figure 5.10 The formula of the model [15]

After that, we want to evaluate website performance based on the model in our thesis by the mathematical model:

Final website performance (%) = + 77.610 + - 0.596 * Response Time + - 0.154 * Load Time + - 0.105 * Broken Link + - 0.415 * Page Size + - 0.013 * Markup Validation + 0.070 * Design Optimization + - 0.051 * No of Request

5.5 Benchmarking

In order to validate a new model in this thesis that called is PEML, we want to compare with the previous studies by using the same dataset in the previous studies [8] [9].

The researchers in the previous studies measured sample data as shown in table 5.3 from national e-government portals of a chosen number of countries in Asia: Singapore, Korean, Japan, Hong Kong, and Malaysia based on many metrics of website performance, consisting of eleven metric: load time, response time, page rank, frequency of update, traffic, design optimization, page size, number of components, accessibility error, markup validation, and broken link. There are five models used in the previous studies [8] [9] : analytical hierarchy process model (AHP), fuzzy analytical hierarchy process model (FAHP), linear weightage model (LWM), hybrid model (combination among LWM and FAHP), and PROMETHEE II model.

As a result, we want to test our new model in this thesis on a new dataset from the previous studies [8] [9] as shown in table 5.4. Table 5.5 the final ranking of e-government websites based on five specific methods from the previous studies and the proposed a new model in this thesis. In accordance with the results generated by the suggested model, Korea website has the highest ranking in comparison with the rest of the e-government websites.

The first column in Table 5.4 shows the metrics of the quality website. The metric elaborate in the website selection process using the proposed model are load time (A), response time (B), design optimization (C), page size (D), number of requests (E), markup validation (F), and broken link (G). The second column shows the measurement unit, and the rest of the columns represent the e-government website performance value

Table 5.4 Original data

Metric	**Measurement unit**	**Singapore**	**Korea**	**Japan**	**Hong Kong**	**Malaysia**
A	**Seconds**	30.77	0.30	68.93	41.94	77.51
B	**Seconds**	1.94	1.17	1.73	1.03	4.84
C	**Percentage**	37.50	57.00	36.50	33.00	22.00
D	**Number**	128,305.00	511.00	285,645.00	195,384.00	366,825.00
E	**Number**	26.00	1.00	60.00	15.00	22.00
F	**Number**	79.00	5.00	21.00	3.00	80.00
G	**Number**	4.00	0.00	1.00	1.00	9.00

Table 5.5 Final result for e-government websites performance

Method	***Singapore***	***Korea***	***Japan***	***Hong Kong***	***Malaysia***
LWM	0.499(3)	0.766(1)	0.456(4)	0.672(2)	0.252(5)
AHP	0.183(3)	0.313(1)	0.115(4)	0.305(2)	0.085(5)
FAHP	0.222(3)	0.390(1)	0.007(4)	0.380(2)	0.001(5)
Hybrid	0.620(3)	0.771(1)	0.431(4)	0.683(2)	0.162(5)
PROMETHEE II	0.019912(3)	0.298043(1)	-0.10962(4)	0.185212(2)	-0.39355(5)
PEML	71.5(3)	80.5(1)	64.9(4)	71.8(2)	61.0(5)

Chapter 6

Conclusion and Future work

This section concludes our thesis. We represent a brief conclusion and future work.

6.1 Conclusion

This study proposed a dynamic model is namely PEML to evaluate the performance of the websites. The proposed approach was using the mathematical model and machine learning. We applied experiments on two algorithms namely, linear regression and support vector machine regression, we applied the experiments on the same dataset that collected to take the best performance of regression methods to generate weight to every the metric for developing a new dynamic model to evaluate websites performance.

6.2 Future work

Future studies can adopt multi-attribute approaches to evaluate the effectiveness of websites and includes adding more metrics to evaluate website performance. The results of future studies then can be compared with those results presented in this study.

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تقييم أداء المواقع الالكترونية باستخدام تعلم الآلة

اعداد: محمد ربحي راتب غطاس

اشراف : د . بديع سرطاوي

الملخص

تلعب مواقع الإنترنت دورًا كبيرًا في مختلف المجالات مثل التجارة، والتعليم، والهندسة والترفيه، ونتيجة لذلك، فإن هناك اهتماماً متزايداً بتصميم الموقع الإلكترونية وتطويرها؛ لتكون فعالة لتقديم درجة عالية من الأداء. لذلك، أصبح الدعم الآلي لمصممي الويب أكثر أهمية لتقييم أداء المواقع الإلكترونية. وعليه، فقد حاولت العديد من الدراسات السابقة تقييم أداء مواقع الويب من خلال تطوير نموذج ثابت، ولم تستطع استخدامه في مجالات أكثر.

أهداف الدراسة:

(1)استكشاف أفضل المقاييس التي تؤثر على أداء موقع الويب.

(2) اقتراح أنموذج ديناميكي لتقييم أداء المواقع باستخدام تعلم الآلة .

(3)مساعدة مصممي المواقع الإلكترونية وصناع القرار على معرفة التحسينات اللازمة لتحسين الأداء والأوزان النسبية النهائية للمقاييس لكل منها على مستوى التسلسل الهرمي.

ولقد اقترحنا في هذه الدراسة، منهجية آلية لتقييم أداء المواقع الإلكترونية باستخدام طريقة تعلم الآلة Machine Learning من خلال تطبيق تجربتين لخوارزميات الانحدار Regression Methods هما الانحدار الخطي المتعدد Multiple linear Regression ودعم انحدار آلة المتجه Support Vector Machineعلى مجموعة البيانات نفسها التي تم جمعها، لأخذ أفضل

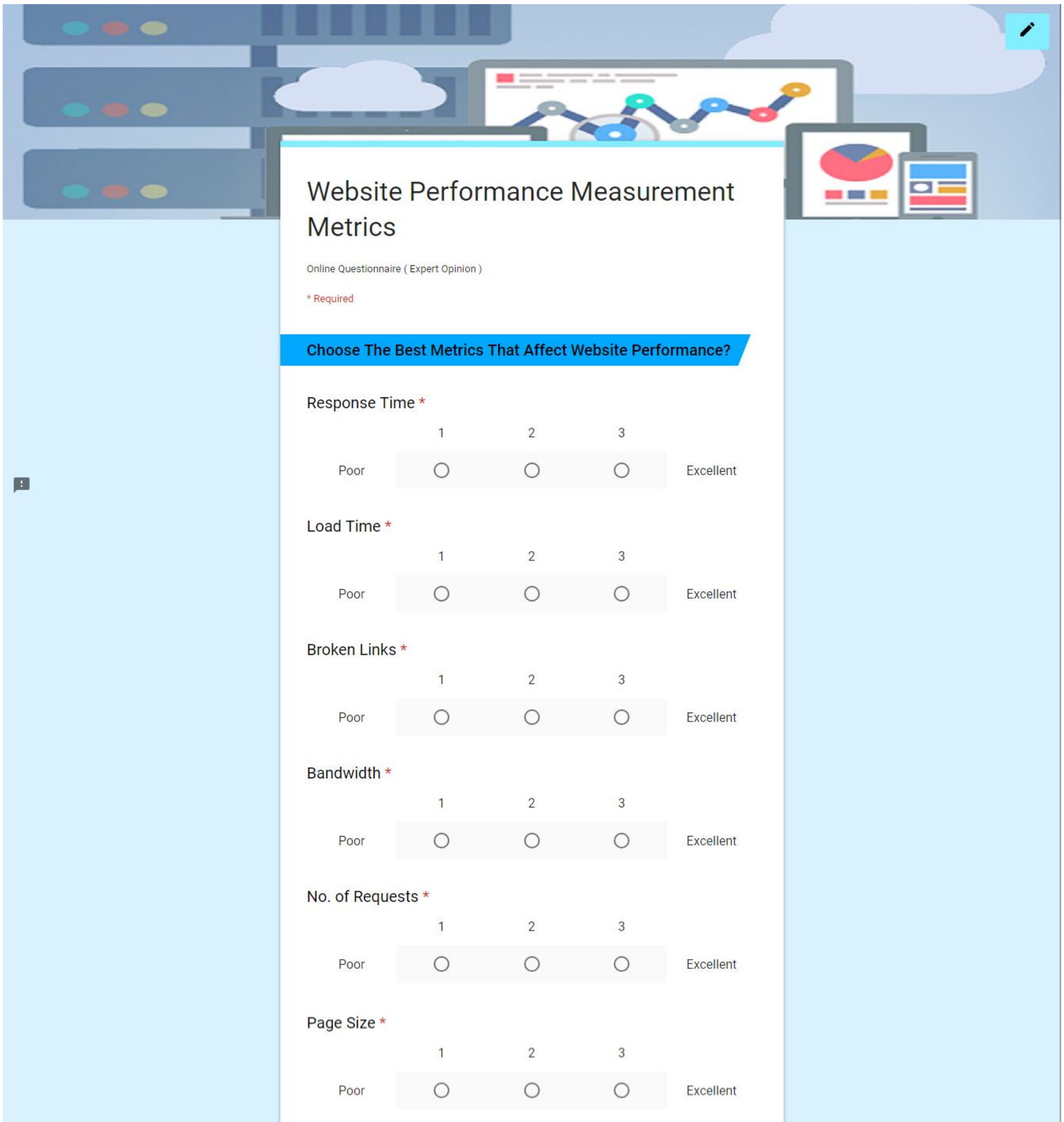
أداء لأساليب الانحدار لتوليد الوزن لكل مقياس، ثم تطوير أنموذج ديناميكي جديد لتقييم أداء المواقع الإلكترونية.

كلمات مفتاحية :

أداء المواقع الإلكترونية، الانحدار، تعلم الآلة، مقاييس الويب، الانحدار الخطي، دعم انحدار آلة المتجه، تقييم، رابيد ماينر.

Appendices:

Appendix 1: Questionnaire Online Form



Website Performance Measurement Metrics

Online Questionnaire (Expert Opinion)

* Required

Choose The Best Metrics That Affect Website Performance?

Response Time *

	1	2	3	
Poor	○	○	○	Excellent

Load Time *

	1	2	3	
Poor	○	○	○	Excellent

Broken Links *

	1	2	3	
Poor	○	○	○	Excellent

Bandwidth *

	1	2	3	
Poor	○	○	○	Excellent

No. of Requests *

	1	2	3	
Poor	○	○	○	Excellent

Page Size *

	1	2	3	
Poor	○	○	○	Excellent

Mark-up validation *

	1	2	3	
Poor	○	○	○	Excellent

Throughput *

	1	2	3	
Poor	○	○	○	Excellent

Design Optimization *

	1	2	3	
Poor	○	○	○	Excellent

DNS Lookup Time *

	1	2	3	
Poor	○	○	○	Excellent

Time To Interact *

	1	2	3	
Poor	○	○	○	Excellent

Time To Title *

	1	2	3	
Poor	○	○	○	Excellent

Time To Start Render *

	1	2	3	
Poor	○	○	○	Excellent

Connection Time *

	1	2	3	
Poor				Excellent

Time To First Byte *

	1	2	3	
Poor				Excellent

Time To Last Byte *

	1	2	3	
Poor				Excellent

The Frequency of Update *

	1	2	3	
Poor				Excellent

Page Rank *

	1	2	3	
Poor				Excellent

Accessibility Error *

	1	2	3	
Poor				Excellent

Availability *

	1	2	3	
Poor				Excellent

Optimal Navigation Times *

	1	2	3	
Poor				Excellent

Total Number of Images *

	1	2	3	
Poor				Excellent

Total Number of HTML Files *

	1	2	3	
Poor				Excellent

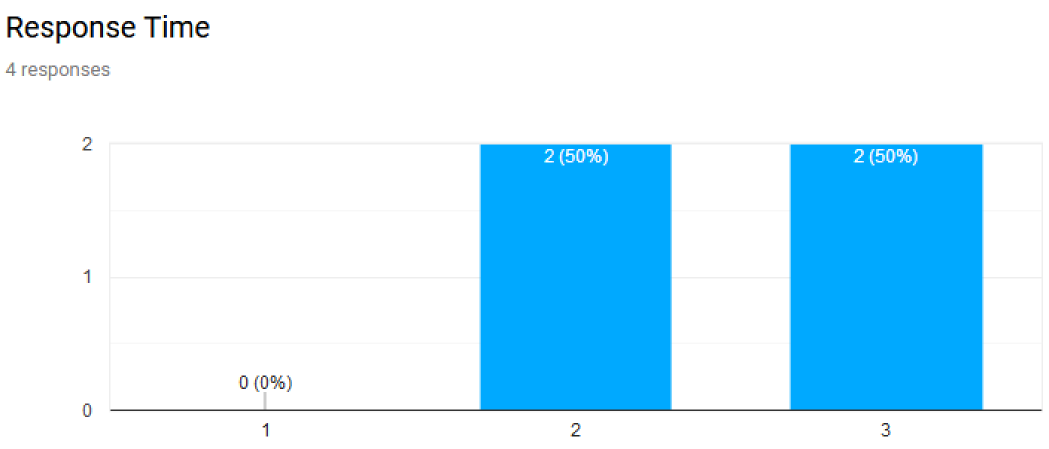
Composition *

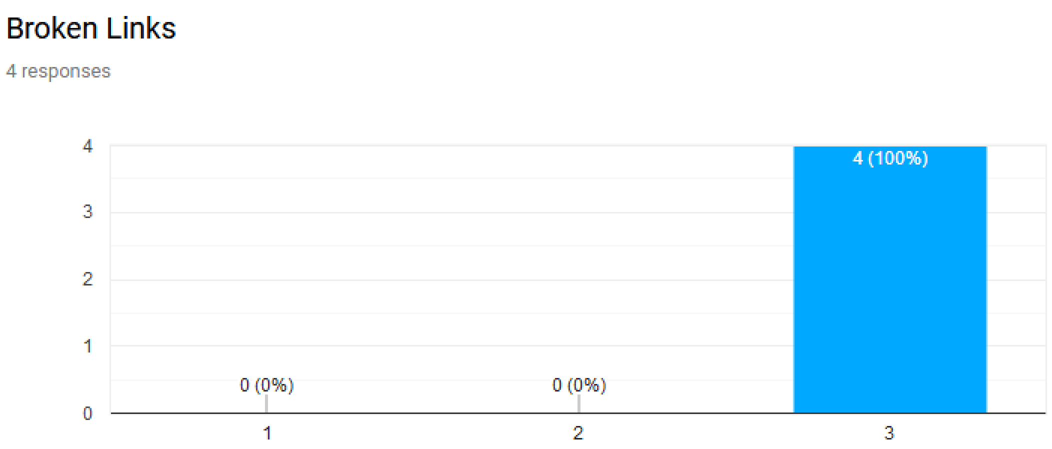
	1	2	3	
Poor				Excellent

SUBMIT

Page 1 of 1

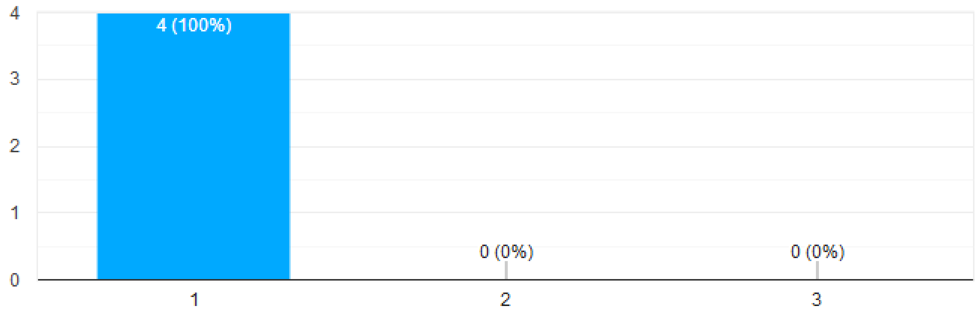
Appendix 2: The Results Questionnaire Online





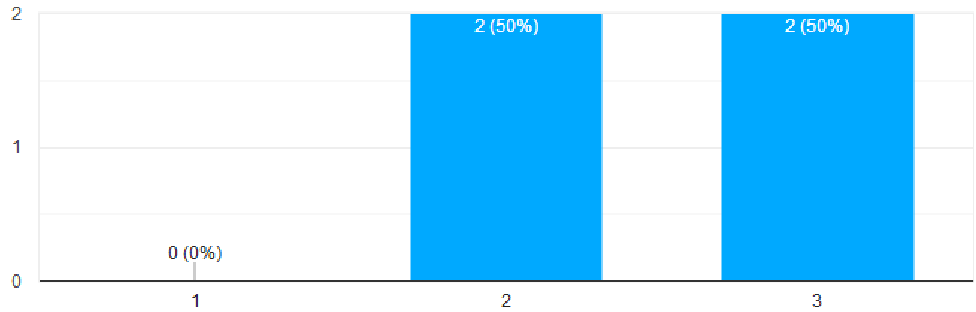
Bandwidth

4 responses



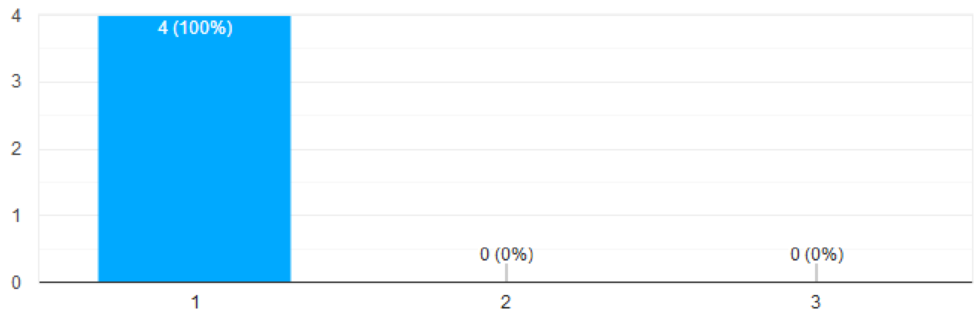
Mark-up validation

4 responses



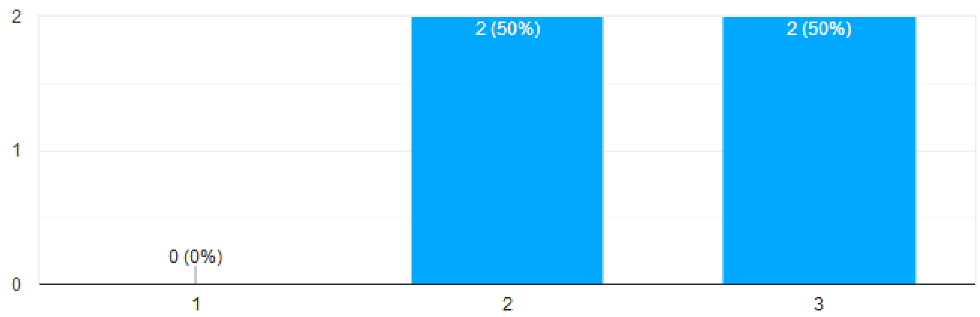
Throughput

4 responses



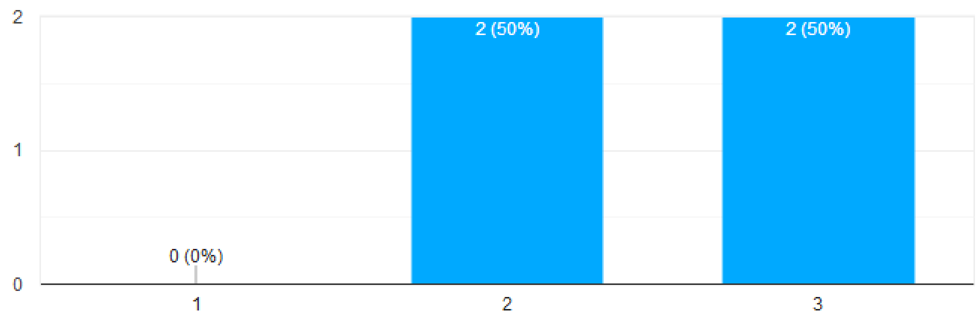
Design Optimization

4 responses



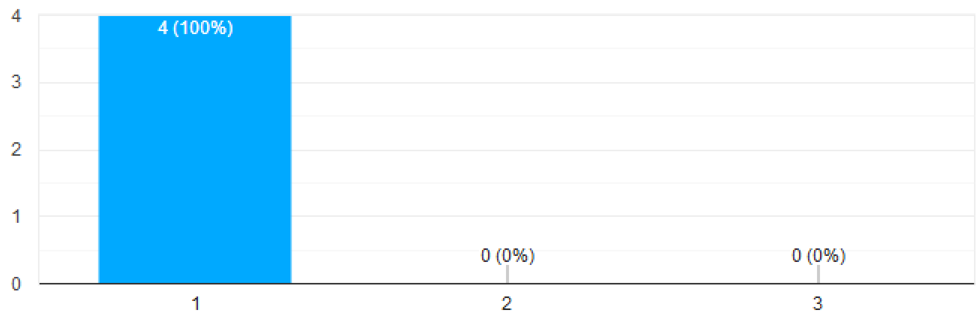
DNS Lookup Time

4 responses



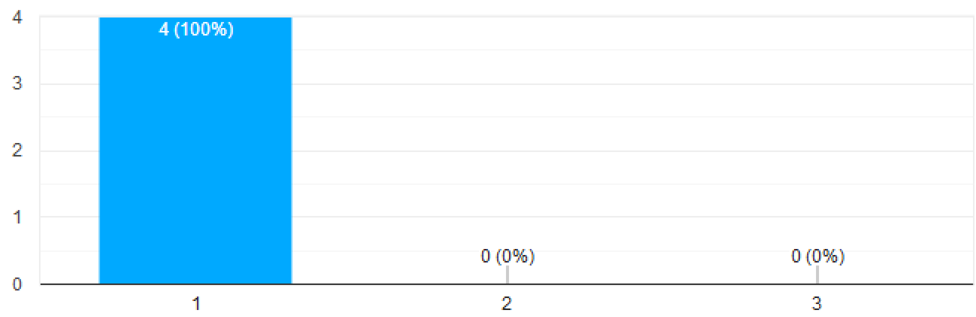
Time To Interact

4 responses



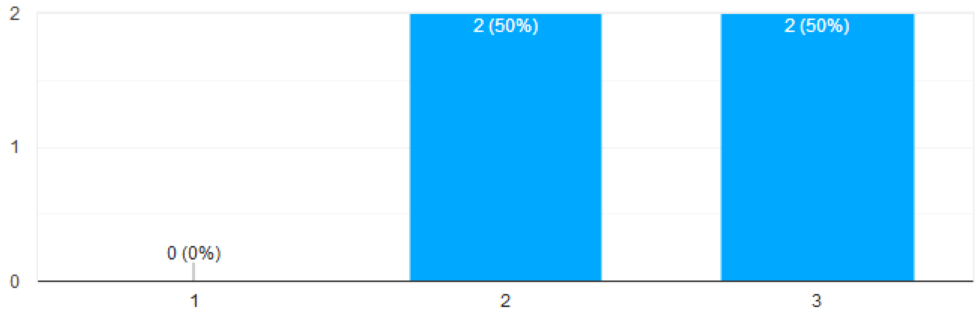
Time To Title

4 responses



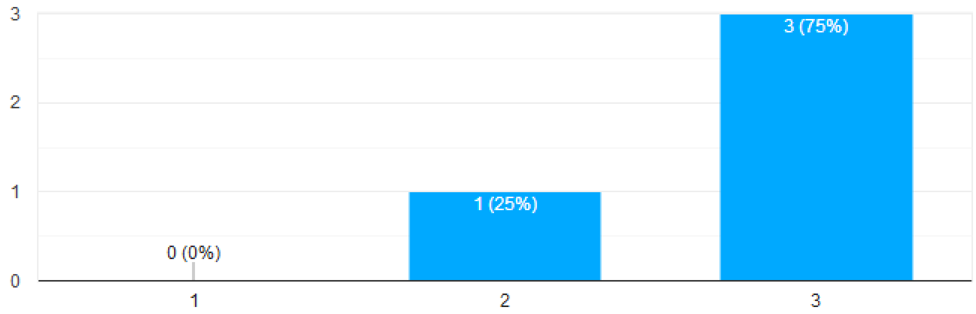
Load Time

4 responses



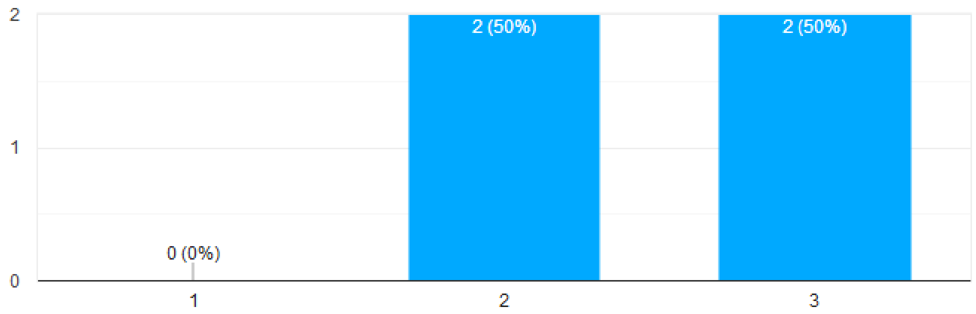
Time To Start Render

4 responses



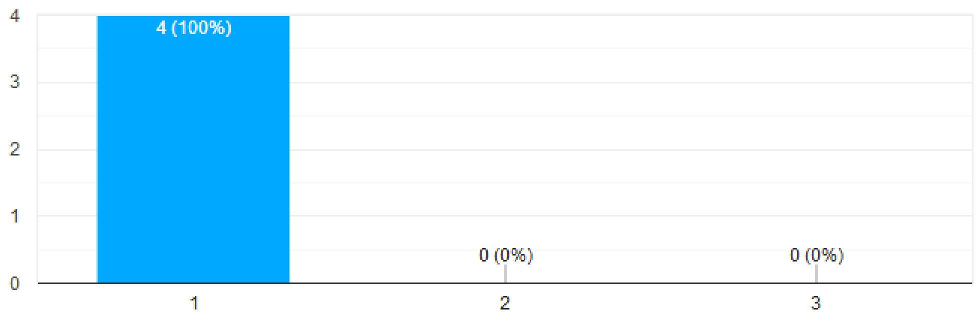
Connection Time

4 responses



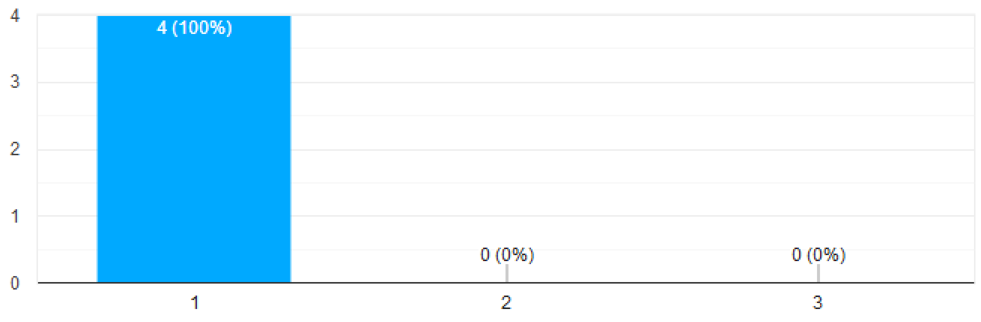
Time To First Byte

4 responses



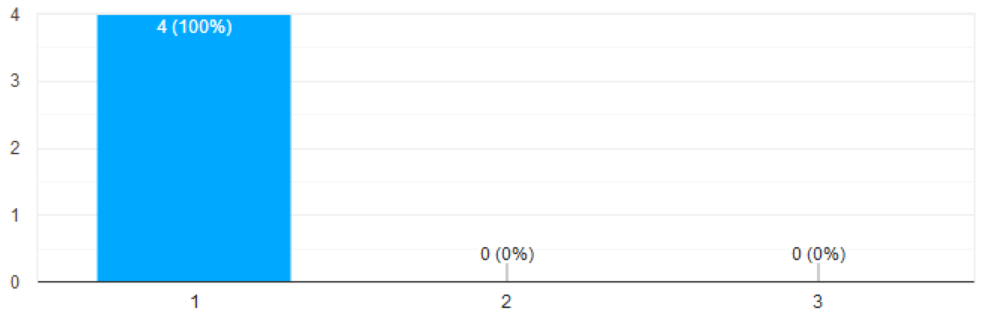
Time To Last Byte

4 responses



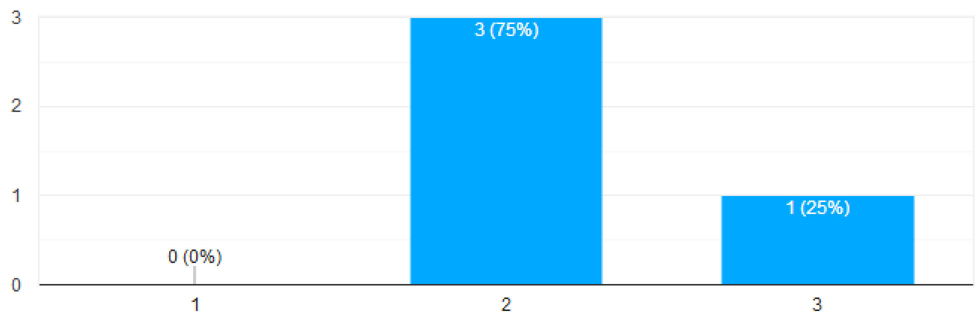
The Frequency of Update

4 responses



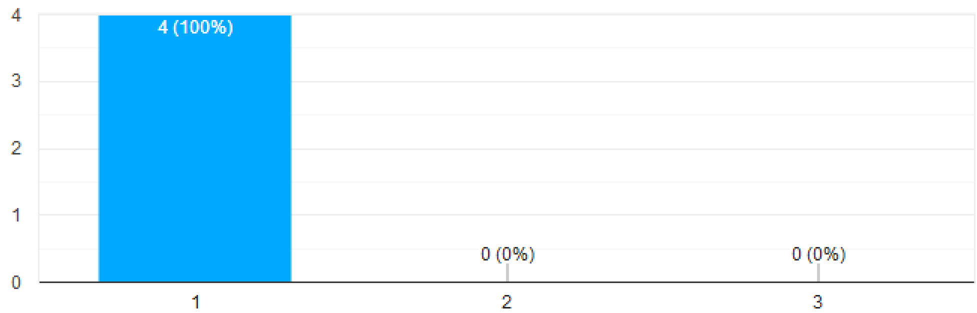
No. of Requests

4 responses



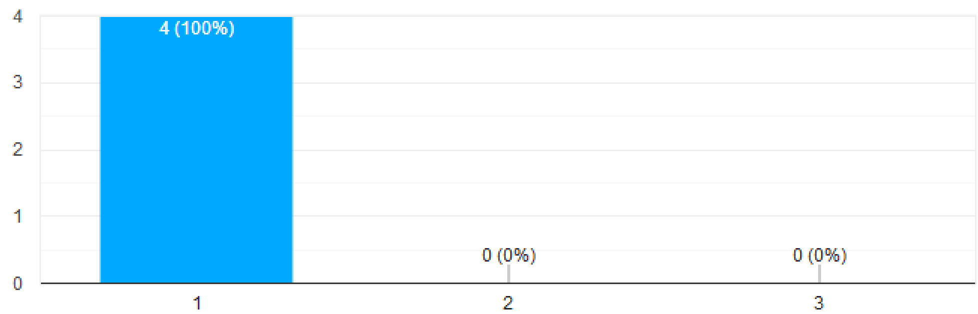
Page Rank

4 responses



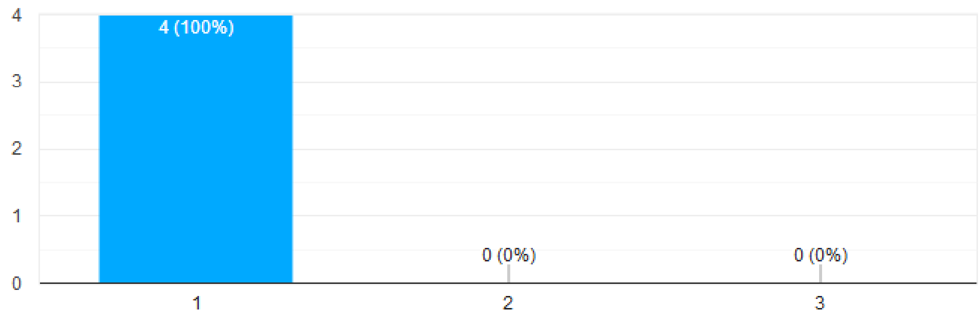
Accessibility Error

4 responses



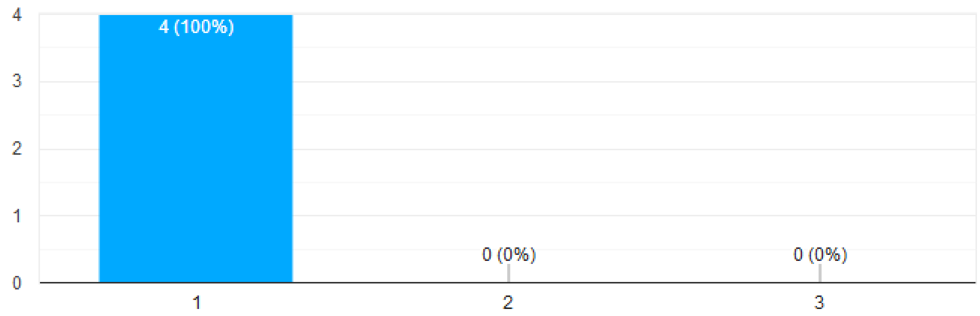
Availability

4 responses



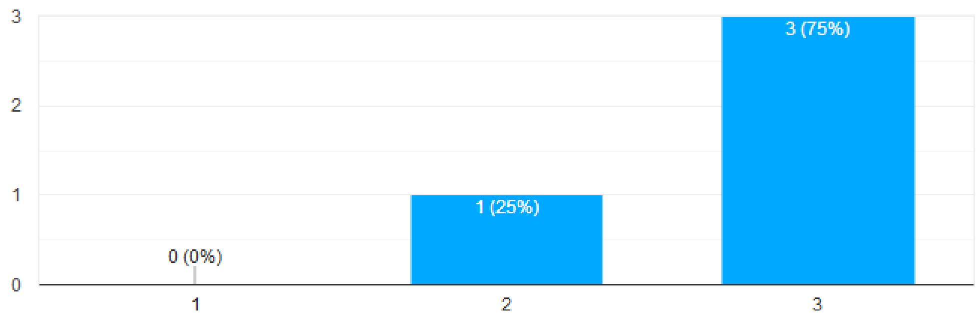
Optimal Navigation Times

4 responses



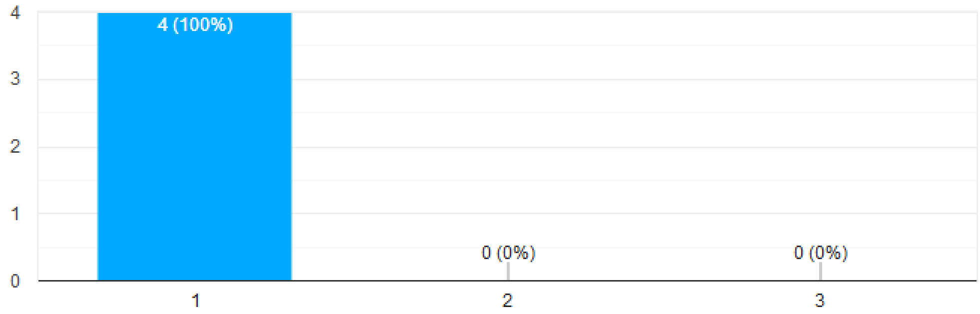
Page Size

4 responses



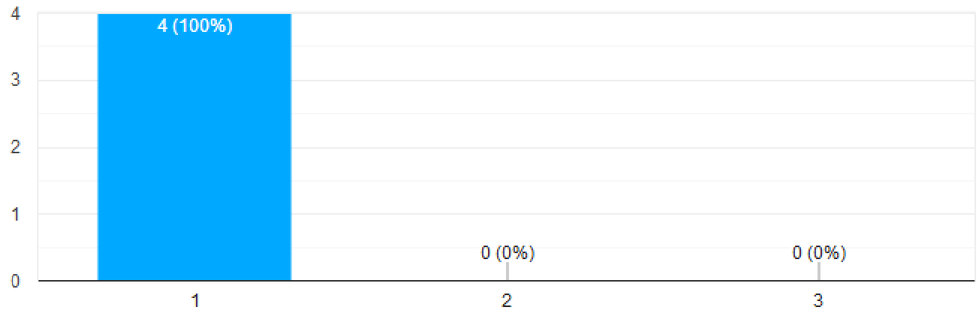
Total Number of Images

4 responses



Total Number of HTML Files

4 responses



Composition

4 responses