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Using Machine Learning in Web Page Categorization for Search Engine Optimization

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ABSTRACT

This research introduces an innovative approach to classifying websites based on their compliance with SEO standards. By merging expert insights with machine learning algorithms, the study develops classifiers capable of accurately sorting web pages into three categories. These classifiers pinpoint key factors that impact the level of page optimization. The training phase entails experts manually labeling data. Experimental findings underscore the efficacy of machine learning in gauging a web page's adherence to SEO guidelines. This method holds significance as it automates the identification of pages needing optimization to enhance search engine rankings. Moreover, the research sheds light on the optimal arrangement of ranking variables utilized by search engines, reinforcing previous research. Additionally, the establishment of a new dataset comprising manually annotated web pages proves invaluable for future research initiatives.

KEYWORDS: Machine learning, on-page optimization, classification, SEO optimization, Search engine optimization.

1. Introduction

The performance and efficacy of web pages are partly reliant on their ranking in search engine results, which in turn hinges on various factors. While these factors are recognized, their precise impact on ranking remains incompletely documented. Search engine optimization experts, often referred to as SEO experts, can typically gauge whether a particular web page has been optimized for specific keywords and adheres to SEO guidelines issued by major search engines, drawing on their experience and expertise. SEO guidelines offer recommendations on how web pages should be structured to facilitate better understanding and ranking by search engine algorithms.

Extensive research in the field of SEO has focused on investigating the significance of web page factors influencing search engine rank. Common research methodologies in SEO involve analyzing characteristics of highly-ranked web pages and conducting experiments to assess how alterations in content affect ranking. In contrast, our research adopted a different approach: leveraging expert knowledge to develop a model for automatically classifying new web pages and extracting pertinent factors influencing their ranking in Search Engine Results Pages (SERP).

The primary objective of our research was to utilize machine learning techniques to construct a classification model capable of automatically categorizing web pages based on their adherence to SEO optimization guidelines. In constructing the model, we incorporated insights from SEO experts. A secondary goal way to identify relevant on-page factors affecting the level of SEO by utilizing the developed classification models. This method of identifying pertinent factors represents a novel approach within the realm of SEO. On-page SEO factors encompass a variety of elements related to web page content, such as text within the page, meta tags, links, images, and code.

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Our research hypothesis posited that by employing machine learning algorithms to classify web pages according to their on-page SEO optimization, we could achieve greater accuracy compared to a baseline. The hypothesis would be validated if the constructed classification model achieved superior accuracy in classifying samples compared to the baseline classification of samples in the majority class.

In line with the research goals and hypothesis, this study aimed to address the following research questions (RQs):

RQ1: What are the key on-page ranking factors that can be identified through the utilization of experts' knowledge and machine learning?

RQ2: Do the identified ranking factors align with findings from previous research?

RQ3: What is the accuracy of the classification models for web pages based on their adherence to on-page SEO practices?

For this research, data were sourced from a random selection of web pages from the DMOZ directory. The directory folder labels were utilized as keywords. Figure 1 illustrates the research workflow.

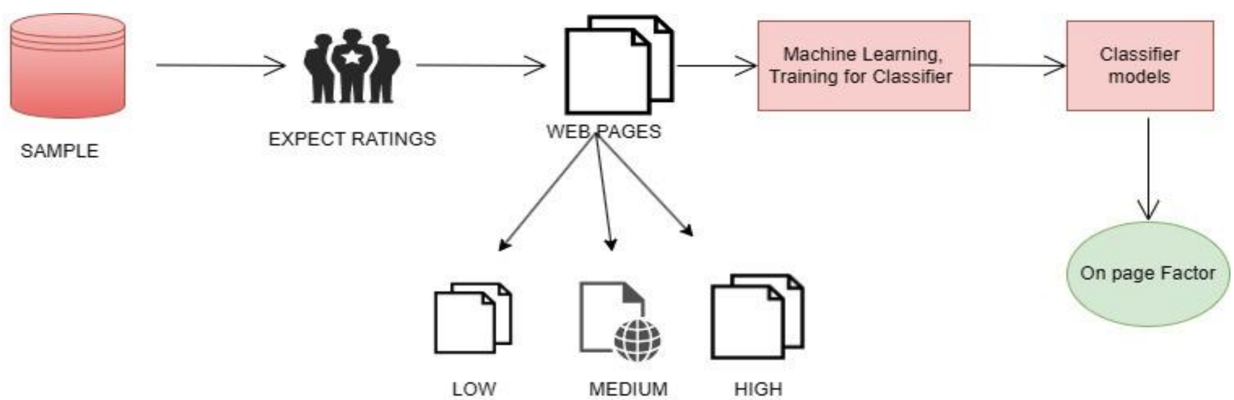

Figure 1 Research workflow.

THE FOUR FUNDAMENTAL APPROACHES:

(1) Selection of an arbitrary test of web pages.

(2) Master Classification of Web Pages.

(3) Advancement and Assessment of Classification Models.

(4) Extraction of Key Variables from Model.

The starting stage included building the dataset by arbitrarily selecting 600 web pages from the DMOZ registry and extricating catchphrases from their category titles. This test estimate of 600 web pages was utilized all through the explore. In the consequent stage, three particular SEO specialists were locked in to survey the SEO quality of the web pages in connection to the indicated catchphrases. They categorized the web pages into three predefined classes: moo, medium, and tall, based on their adherence to on-page SEO rules. The dataset made in this stage served as input for the consequent stage, which included developing classification models utilizing different machine learning algorithms.

The results of the classification stage were at that point utilized in the last stage, where noteworthy variables affecting classification were extricated and assessed from web pages categorized as having the most elevated SEO quality — those classified into the tall lesson. In spite of the fact that the inquire about was conducted on English web pages, the strategy proposed is versatile and can be connected to web pages in other dialects as well.

2 LITERATURE SURVEY

Exploring the junction of search engine optimization (SEO) and machine learning through a literature survey unveils a vibrant landscape characterized by innovation. Here, traditional SEO tactics are undergoing a transformation, bolstered by the integration of advanced machine learning algorithms. At its core, SEO remains pivotal for digital visibility, encompassing strategies aimed at elevating a website's ranking on search engine results pages (SERPs) and fostering user engagement. As the digital realm continues to expand and competition for online visibility intensifies, the infusion of machine learning into SEO practices has emerged as a promising avenue for gaining a competitive advantage. Foundational SEO principles, including keyword optimization, content quality enhancement, backlinking, and website structuring, serve as the groundwork for understanding how machine learning can enhance and optimize these strategies. However, machine learning introduces a fresh perspective to SEO by harnessing data-driven insights and predictive analytics to refine various aspects of search engine performance.

Furthermore, journal papers have examined the intersection of SEO with other disciplines, such as machine learning, data mining, and information retrieval, to develop more advanced and effective optimization strategies. Additionally, the ethical implications of certain SEO practices, such as black hat SEO tactics, have been a subject of inquiry in academic literature.

2.1 On-Page Factors

Web page substance characteristics, comprising content, joins, pictures, tables, navigations, URLs, record names, and HTML code, drop inside the domain of on-page variables, completely overseen by the webmaster. These variables are underscored in rules issued by look engines.

- Text quality (counting data quality),
- Clear navigation,
- Page title (HTML “title” tag),
- Meta-description (HTML “meta description” tag),
- Using H tag for checking titles (H1, H2, H3, etc.),
- ALT property on pictures (brief picture description),
- Anchor content of links,
- URL (address) of the page (counting the space name),
- Web page stacking speed, and
- HTML code-to-content proportion (must be in favor of the content).

Web page substance characteristics, comprising content, joins, pictures, tables, navigations, URLs, record names, and HTML code, drop inside the domain of on-page variables, completely overseen by the webmaster. These components are underscored in rules issued by look engines.

2.2. Off-Page Factors

Off-page factors play a significant role in today's search engine algorithms, influencing a web page's ranking based on external impacts rather than its content. These factors, which are largely beyond the control of the web page author, include incoming and outgoing links, their quality, and recommendations from social media platforms. Early algorithms like Page Rank and HITS treated links as "votes", assuming that web pages with more links were more authoritative and deserving of higher positions in search results.

While off-page factors are crucial in determining a web page's visibility and ranking, this paper does not delve into them extensively as they were not the focus of the research.

2.3. Factor Keywords

The SEO process typically commences with keywords, which are the words or phrases internet users input when seeking information on search engines. These keywords, often expressed as queries or questions, guide users to relevant content. While questions are becoming increasingly utilized, keyword searches remain prevalent, typically consisting of two to three words for optimal results. To attain visibility in organic search engine results, web pages must incorporate relevant keywords across both on-page and off-page elements. SEO fundamentally revolves around identifying keywords that elevate a page's ranking in search engine results.

Keywords play a pivotal role across various domains, aiding in the identification of spam, malicious content, and fake news, as well as in manipulating search engine algorithms through unethical practices known as "black hat SEO." Keyword suggestion systems have been developed to categorize web pages by topic or to assist in the SEO process, often extracting keywords from catalog categories rather than page content.

3. Machine Learning

Machine Learning rotates around refining calculations utilizing real-world information, drawing from disciplines like measurements, information science, and databases. Its principal objective is to engage machines to extrapolate experiences, figure results, and observe designs from information. This space envelops two essential approaches: directed and unsupervised learning. Administered learning includes named information for anticipating future values based on free factors. It handles both relapse and classification issues, with straight relapse being communicated scientifically as

$$y=w0+w1x1+w2x2+...+wnxn \quad (1)$$

where y is the subordinate variable; x1, x2, …, xn are free factors; and w0, w1, …, wn are weight factors.

In unsupervised learning, the subordinate variable y remains undisclosed inside the dataset. Or maybe than foreseeing the subordinate variable, unsupervised learning points to reveal critical structures inside the information. A prime illustration of this approach is clustering calculations, which categorize information based on their inherent characteristics (autonomous variables). In classification issues, a subordinate variable y is alloted names comparing to one (single-label classification) or more (multi-label classification) pre-defined classes, decided by the values of autonomous factors. In our ponder, we utilized single-label classification, wherein websites were categorized into one of three pre-defined classes.

The center of this paper centers on on-page alterations of web pages agreeing to SEO rules. We portrayed three classes of alterations: moo, medium, and tall SEO alterations. SEO specialists labeled the information concurring to their individual classes. As the subordinate variable was ostensible, classification strategies were utilized to construct the models. The ensuing segment presents a brief diagram of well known classification strategies utilized in information science and computerized promoting, which were moreover utilized in this research.

3.1. Classification Methods

3.1.1. Decision Trees

Decision trees stand out as one of the foremost classification methods renowned for yielding interpretable outcomes. These trees comprise decision nodes that branch out successively until they culminate at the leaves, or nodes, at the lowest tier, where a specific class is assigned. Such trees serve the purpose of classifying new data samples (instances).

Among the most prevalent decision tree algorithms are ID3, C4.5, CART, CHAID, and QUEST. While capable of regression tasks, their primary utility lies in classification endeavours. Decision trees boast several advantages, including their interpretability (facilitating easy explanations), lack of underlying data assumptions, and resilience against outliers. Nonetheless, they exhibit drawbacks such as sensitivity to data diversity, potential complexity and sluggishness in training, and a tendency to over fit unless pruned appropriately.

3.1.2. Naive Bayes Classifier

The naïve Bayes classification method operates on the principles of Bayes' conditional probability theory, initially assuming that all attributes (variables) are independent and of equal importance. Widely utilized in information retrieval, this technique applies the Bayes conditional probability rule to make predictions.

Equation (2) represents the conditional probability relationship between events A and B according to Bayes' theorem. In the context of a classification problem, where A represents the class variable y and B represents the vector of independent variables X, the goal is to compute the class probability of a sample given the values of the independent variables. Naïve Bayes classification is a probabilistic method that yields class probabilities as results, contrasting with "hard" algorithms that directly predict a sample's class.

If the assumption of feature independence holds true, naïve Bayes classifiers can perform well and learn quickly, especially with categorical variables, offering a key advantage. However, if this independence assumption is invalid, the algorithm's performance may suffer. Additionally, a drawback is the "zero frequency" issue: if a categorical variable value was absent from the training set, the model will assign a probability of zero to that value.

3.1.3. K-Nearest Neighbor Method

The k-nearest neighbor method (KNN method) is a classification technique that doesn't create a model upfront. Termed a "lazy" algorithm, it predicts the class for a new sample as soon as it's introduced. This prediction is made by computing distances between the new sample and others in the dataset across n-dimensional space, where n represents the number of variables. Once all distances are calculated, only the k-nearest neighbors are considered, and their classes are decided by majority voting. Typically, the Euclidean distance is the preferred metric in this method.One advantage of KNN is its simplicity in implementation since it doesn't require a training period. However, it's noteworthy that KNN can be slow in performance, particularly with large datasets and those with high dimensionality.

3.1.4. Support Vector Machines

Support Vector Machine (SVM) is a machine learning algorithm used in classification and regression tasks. It operates by finding the optimal hyperplane that separates data points into different classes while maximizing the margin, which is the distance between the hyperplane and the nearest data points, known as support vectors. By maximizing this margin, SVM aims to generalize well to unseen data and mitigate overfitting. SVM can handle both linearly separable and non-linearly separable data by utilizing kernel functions that map the input space into a higher-dimensional feature space where the data becomes separable. This ability makes SVM effective in various domains, including text classification, image recognition, and bioinformatics. Furthermore, SVM's decision boundary is influenced by the support vectors, making it robust to outliers in the dataset. However, SVM's computational complexity increases with the size of the dataset, particularly for large-scale problems, and selecting the appropriate kernel function and hyper parameters requires careful tuning. Despite these challenges, SVM remains popular due to its effectiveness in high-dimensional spaces, ability to handle non-linear data, and solid theoretical foundation in statistical learning theory.

3.1.5. Logistic Regression

Logistic regression utilizes the logistic function for classification due to its S-shaped curve, facilitating the creation of a model that outputs probabilities ranging from 0 to 1. When employing classical linear regression for binary classification, probability values outside the [0, 1] range can arise, which is illogical for classification purposes. Hence, the logistic function addresses this by constraining the output within a valid probability range.

The logistic function, denoted as l(x), is expressed as e^ (w0 + w1x) / (1 + e^(w0 + w1x)), where w0 and w1 are weight coefficients, and x is the independent variable. Unlike linear regression, where weights are determined through the least squares method, logistic regression employs the maximum likelihood method. This approach estimates w0 and w1 to ensure that the logistic function output for positive instances approaches 1 and for negative instances approaches 0.

Logistic regression's strengths lie in its simplicity, ability to provide probability outputs, and reduced susceptibility to overfitting in low-dimensional datasets. However, it may encounter overfitting challenges with high-dimensional datasets. Despite this limitation, logistic regression remains a widely used and effective tool for binary classification tasks.

3.1.6. Artificial Neural Networks

Artificial Neural Networks are comprised of artificial neurons, or units, arranged in layers that collectively form the network. The size of each layer can vary significantly, from just a few units to millions, depending on the complexity of the patterns the network needs to learn from the dataset. Typically, an Artificial Neural Network includes an input layer to receive external data, hidden layers for processing, and an output layer to provide responses. Data flows from the input layer through the hidden layers, where it undergoes transformations, before reaching the output layer. Throughout this process, connections between units in different layers carry weighted influences, with these weights determining the extent of influence one unit has on another. As data is passed through these interconnected units, the network gradually learns about the dataset, ultimately producing an output through the output layer.

3.2. Classification Evaluation

Different classification calculations in fact display changing exhibitions depending on variables such as the space, characteristics of the dataset, and presumptions of the calculation. Thus, there isn't a all around prevalent calculation; the choice depends on the particular utilize case and requires evaluation.

Evaluation of a classification show regularly includes testing it on a partitioned dataset from the one utilized for preparing. Two common procedures for this reason are the hold-out strategy and cross-validation.

- Hold-out strategy: This includes part the dataset into two sets some time recently preparing: one for preparing the show and the other for validation.
- Cross-validation: Here, the preparing set is isolated into k parts, and the demonstrate is approved k times. Amid each emphasis, k - 1 parts are utilized for preparing, and the remaining portion is utilized for approval. The assessment measurements are at that point found the middle value of over the k iterations.

Regardless of the testing strategy utilized, a few measurements are commonly utilized for classification evaluation:

1. Accuracy: Measures the in general rightness of the model's predictions.
2. Precision: Measures the extent of genuine positive expectations among all positive expectations made by the model.
3. Recall: Measures the extent of genuine positive forecasts among all genuine positive instances.
4. MAE (Cruel Outright Blunder): Normal of the supreme contrasts between anticipated and real values.
5. MSE (Cruel Square Blunder): Normal of the squares of the contrasts between anticipated and genuine values.

These measurements give bits of knowledge into distinctive perspectives of the model's execution, making a difference to evaluate its viability in different contexts.

4. Research Methods

This research unfolded in four distinct phases: initially, a random sample of web pages was drawn from the data source. Subsequently, three SEO experts categorized these pages into three predefined classes during the rating phase. Following this, classification models were developed and subjected to evaluation. Finally, in the last phase, significant factors were gleaned from the constructed models.

4.1. Data Set Forming

For this research, a dataset was constructed through the random sampling of 600 web pages sourced from the DMOZ directory. DMOZ, commonly utilized in information retrieval and web page classification, offers a comprehensive array of web pages categorized by topic, making it an ideal resource for tasks such as text summarization and keyword extraction. It's worth noting that this study focused exclusively on English-language web pages; however, the models developed herein possess applicability to web pages across all languages.

The dataset's composition across various categories is detailed in Table 1. To ensure specificity and relevance in keyword extraction, the sampling process targeted categories at a minimum of the third level of the hierarchical structure within DMOZ. This strategic approach helped mitigate the risk of employing overly broad keywords that might fail to accurately describe the content at the desired level of granularity. Additionally, certain categories such as "Regional", "World", and "News" were deliberately excluded from the sampling due to their inherent characteristics; for instance, the "News" category primarily comprises news portals, posing challenges in keyword determination from its content.

Category	**Number of Pages**
Arts	63
Business	69
Computers	58
Games	35
Health	59
Total	**600**

During this phase, keywords were generated for each web page based on its category title, ensuring a minimum categorization depth of the third level within the DMOZ hierarchy. In instances where category titles comprised multiple words, they were parsed accordingly, as illustrated in examples. Moreover, common stop words were disregarded from the category titles during this process. If a web page happened to be associated with multiple categories, only the first one encountered, meeting the specified criteria (third level or lower), was considered. As a result of this phase, a dataset consisting of 600 URLs, each accompanied by its corresponding keywords, was compiled.

4.2. Rating Web Pages

In this phase, three independent SEO experts undertook the task of categorizing the web pages from the dataset into three predetermined classes: "low SEO," "medium SEO," and "high SEO." Their assessments were based on the provided target keywords, SEO guidelines, as well as their subjective evaluations, expertise, and professional perspectives. Expert 1 operates an SEO agency in Croatia, while Experts 2 and 3 are employed by SEO agencies in India.

The outcome of this classification phase resulted in the formation of a dataset comprising three attributes: URL, keywords, and the assigned class label. The distribution of class labels within the dataset is outlined in Table 2.

Class	**Expert 1**	**Expert 2**	**Expert 3**
LOW SEO	180	119	**112**
MEDIUM SEO	307	341	**341**
HIGH SEO	113	140	**147**
TOTAL	600	600	**600**

Table 2 shows the number of cases for each course esteem as named by three free specialists, along with the amassed number of illustrations based on larger part voting of the names from the three experts.

4.3 Independent Variables Selection

The independent variables selected for training the classification models are detailed in Table 3, categorized by their respective groups and accompanied by their variable codes and descriptions.

Group	Variable Code	Description
Page header	Tlen	Length of substance in the HTML "title" tag (word count)
Headings	h1	Number of events of HTML H1 tag
Images	Alt	Keyword recurrence in the ALT attribute
Links	Linkkw	Keyword recurrence in the stay text

The dataset encompassed 600 instances, delineated by 21 independent variables and 1 dependent variable. Following a correlation analysis among the variables, it was observed that only a limited number of variable pairs exhibited a correlation exceeding 0.5.

4.4. Extraction of On-Page Factors

Analyzing a dataset can unveil the relative importance of different factors (independent variables) in predicting classes. One straightforward approach is to rank variables based on their correlation with the class variable. However, another effective method involves employing decision trees and assessing prediction properties of individual variables. Decision trees use measures of variable importance to determine which attributes should be utilized for splitting. Information gain, a common measure, quantifies the reduction in entropy resulting from splitting on a particular attribute. By constructing multiple trees on subsets of the data, known as "random forests," and averaging the results, variance in tree-based methods can be reduced, leading to more robust outcomes. Alternatively, the "Relief" algorithm, which relies on nearest-neighbor techniques, assigns relevance weights to each feature to detect important variables. Chi-square is also frequently utilized in machine learning to gauge the relationship between predictors (independent) and the target variable (dependent). By employing these various methods, researchers can effectively identify and prioritize the most influential variables for class prediction, thereby enhancing the overall accuracy and reliability of their models.

5. Evaluation Results

The model evaluation process encompassed both the hold-out method and cross-validation techniques. In the hold-out method, two-thirds of the dataset were allocated for training the model, while one-third was reserved for validation. Cross-validation employed a 10-fold nested approach, comprising 10 iterations in both the inner and outer loops. Training of the classification models was conducted utilizing the MLR package within an R environment. Five classification algorithms were employed: decision trees, Support Vector Machine (SVM), Naïve Bayes, KNN (K-Nearest Neighbors), and logistic regression. Evaluation of these classifiers relied on classification accuracy as the primary metric. Hyper parameters for all classifiers were fine-tuned using the grid search method, while data normalization was performed using the min-max method. Stratification was employed in cross-validation to ensure balanced representation of class labels.

To assess the suitability of the dataset size, learning curves were generated and plotted for each classifier, as depicted in Figure 1. These learning curves provide valuable insights into the relationship between model performance and dataset size, aiding in the optimization of model training and dataset selection processes, as shown in Figure 1.

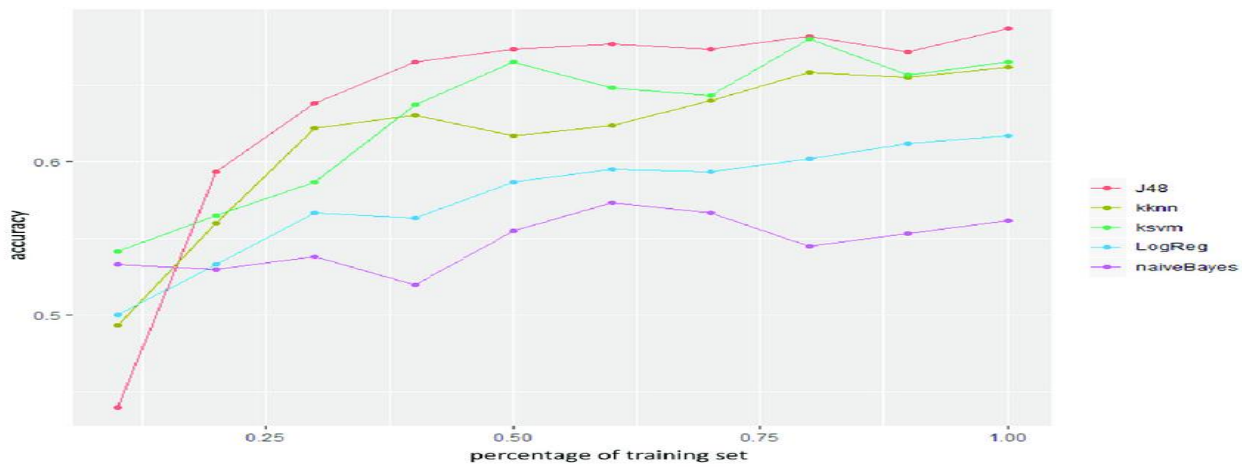

Figure.1 Learning curve used for classification algorithms.

Observing Figure 1, It's evident that the accuracy experienced a rapid increase, reaching approximately 50% of the training set size. This trend suggests that the data set size employed in our research was appropriate.

To validate our research hypothesis, we compared the results of the five classifiers with a baseline accuracy derived from the "ZeroR" algorithm, which serves as the simplest model in machine learning. This algorithm predicts the class with the highest frequency, often referred to as the majority class. In our study, this majority class corresponds to "medium SEO," observed in 293 out of 600 instances, constituting 48.83% of the dataset. During 10-fold cross-validation, we found that the average accuracy of all five classifiers exceeded this baseline threshold, as depicted in Figure 2. Here, the red line represents the baseline accuracy (48.83%), while the central line in the boxes signifies the median, and the dot indicates the average accuracy. Notably, the median (and average) accuracy values for all classifiers lie above the red line, suggesting, as indicated by reference, that our hypothesis holds true: the classification models developed for categorizing web pages based on their SEO optimization level exhibit higher accuracy than mere majority class classification.

However, to solidify these findings, further evaluation through statistical tests is imperative to draw statistically significant conclusions.

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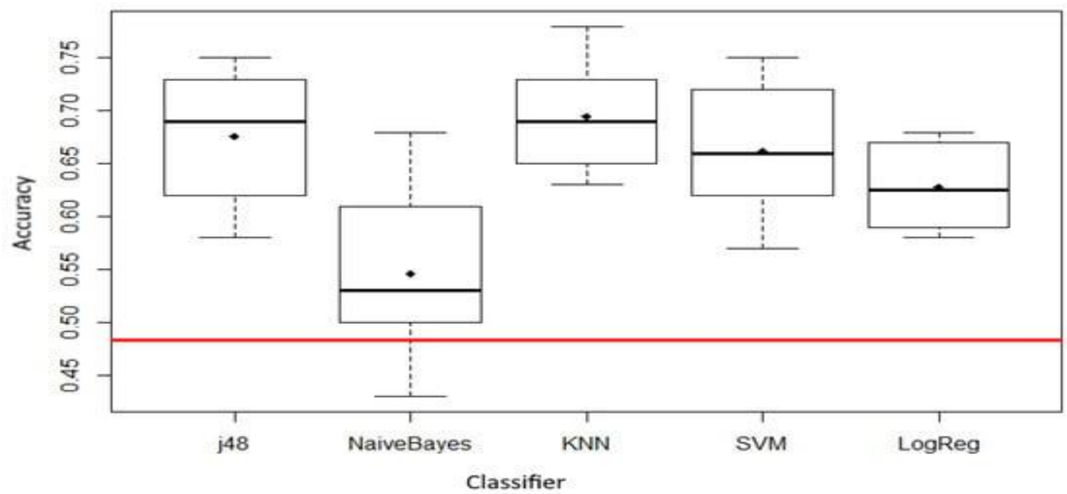

Figure 2 Comparison of precision of classifiers utilizing 10-folds' cross approval with standard exactness (ruddy line).

When researchers compare multiple classifiers on a single dataset, they often turn to either parametric or non-parametric tests for dependent samples. While the t-test is a traditional choice, it requires adherence to normal distribution assumptions, which weren't feasible in our study. Thus, we opted for non-parametric tests. These tests are appropriate when a separate validation dataset exists, making them unsuitable for cross-validation. Therefore, our research exclusively utilized the hold-out validation method, which involved creating contingency tables for each classifier pair to evaluate their performance against the baseline accuracy.

We established a critical threshold, X2 > 3.841 (representing the chi-squared distribution with 1 degree of freedom and $\alpha = 0.05$), to determine with 95% confidence whether classification accuracy significantly differed from the baseline accuracy. Our results indicated such deviations for all classifiers except Naïve Bayes, which displayed relatively inferior performance.

6. Conclusions

In conclusion, this research explored the application of machine learning in assessing the degree of web page optimization to SEO guidelines. Classifiers trained on a dataset of 600 web pages, categorized into "low SEO," "medium SEO," and "high SEO" by SEO experts, achieved accuracies ranging from 54.69% to 69.67%, surpassing the baseline accuracy of 48.83%. The study validated the efficacy of using machine learning classification algorithms, informed by expert knowledge, to predict web page SEO optimization. Additionally, a decision tree algorithm was employed to extract relevant SEO factors. The dataset generated in this research holds potential for further exploration of on-page ranking factors in SEO research. Importantly, the methods employed are not specific to any particular search engine or language. They can be adapted to target specific search engines by instructing SEO experts to classify web pages accordingly. Similarly, the methods can be extended to different languages with the development of stemming or lemmatization algorithms for those languages.

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