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IRHM: Inclusive Review Helpfulness Model for Review Helpfulness Prediction in E-commerce Platform

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Abstract

Online reviews have become essential aspect in E-commerce platforms due to its role for assisting customers' buying choices. Furthermore, the most helpful reviews that have some attributes are support customers buying decision; therefore, there is needs for investigating what are the attributes that increase the Review Helpfulness (RH). This research paper proposed novel model called inclusive review helpfulness model (IRHM) can be used to detect the most attributes affecting the RH and build classifier that can predict RH based on these attributes. IRHM is implemented on Amazon.com using collection of reviews from different categories. The results show that IRHM can detect the most important attributes and classify the reviews as helpful or not with accuracy of 94%, precision of 0.20 and had excellent area under curve close to 0.94.

Keywords: Review helpfulness, Recommender system, Machine learning, Sentiment analysis.

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Introduction

Online reviews are become important factor of assisting customers' buying decisions. Reviews offers valuable information that can influence customers' opinion. Moore in (Moore, 2015) states that 92% of customers nowadays read online reviews. This makes online review helpfulness more key factor in E-commerce platform. Moreover, online reviews differ in their support to customers due to different subjective. For example, some of customers discover the reviews that support their decision-making such as product evaluation reviews. In other words, they looks for its utility that called "Review Helpfulness" (Baek, Ahn, & Choi, 2012). RH indicates whether the review gives useful product assessment and buying decision to other customers. Hence, it is important to explore attributes and what make the review more helpful. These attributes belong to two major categories: the first is about the review itself such as review length, rating valence, and review extremity (Cao, Duan, & Gan, 2011). The second is related to reviewers such as reviewer image , reviewer ranking, and reviewer engagement (Salehan & Kim, 2016). This research proposes a novel model called IRHM that handle every RH classification problems. The outcome of IRHM is a skillful classifier used to predict the RH in any E-commerce platform according to the most important attributes affect the RH. The paper will present RH concept, then the similar works will be revised and research gap will be identified in literature review.

The reset of this paper is organized as: section 2 is a general overview of RH, while the literature review and related work are presented is section 3. After that IRHM and its phases will be detailed in section 4. IRHM implementation and performance are presented in sections 5 and 6 respectively. Finally, discussion and conclusion in sections 7 and 8.

Review Helpfulness (RH)

Review is defined as the process of examination, report, survey or evaluation of product or service posted in E-commerce platform. Additionally, Review "helpfulness" answers whether a review gives product assessment and buying decision to customers (Filieri, 2015). In other words, review effectiveness is not equal in their value to consumers. Some customers are more interested to reviews seeming more helpful to them. Therefore, websites that categorize the helpful reviews gain higher consumer attention (Yin, Bond, & Zhang, 2013).

In a voting system, as the one proposed by Amazon (Ghose & Ipeirotis, 2011), RH can be defined as given in equation 1:

$$H = \frac{np}{np + nn} \tag{1}$$

Where np represents the number of positive votes and ***nn*** is number of negative votes (Kim, Pantel, Chklovski, & Pennacchiotti, 2006). While this approach is simple and good enough, it still shows some shortcoming, such as the lack of votes for new reviews (Li, Huang, Tan, & Wei, 2013) and the fact that not everyone who reads reviews actually votes on them (Kim et al., 2006). For that reason, the most-voted review systems are not necessarily reflecting the accurate representation of the most helpful ones. So, there is need to dig in experiments answer the question of what are the actual attributes that make the review helpful to customers.

Literature review

Many researches highlight the impact of different attributes on the RH. Some of these attributes are related to review itself and others are related to reviewer who writes this review. In this context, we will review the most important attributes have been confirmed to have significant impact on RH. Review attributes display all criteria that are related to written text of the review. The attributes may differ from platform to another according to the nature of this platform. In addition, review attributes can affect RH in different percentage due to the power of this attribute.

First, (Salehan & Kim, 2016) focused on the following attributes: Title length, Review sentiment, Title sentiment, Longevity, Review length, Review polarity and Title Polarity. They found that negative sentiment influences the performance of online reviews. Other study by (Wu, 2017) examined three determinants as: Review attributes (Valence, Depth, and Life), Reviewer attribute (Credibility) and Review hosting website attribute. (Zhang & Zhang, 2014) experimented the helpfulness of reviews according to the following variables: Consumer rating, Name, Product review, Date, Reviewers' ranking, Reviewers' helpful vote percentage, Review number, Helpful vote and Total vote. While (Gao, Hu, & Bose, 2017) aimed to examine whether attributes can be used to predict the helpfulness of future reviews. They addressed review length, ratings, and equivocality that proved to have significant effect on RH.

On other hand, in (Ghose & Ipeirotis, 2011) explored how the review and the self-reported characteristics of the reviewer can affect online community and social behavior such as RH. To examine this, they collected data from Amazon.com and analyzed the associated review system. For each review, they retrieved the actual textual content of the review and the review rating of the product given by the reviewer. The textual analysis of reviews includes Readability and Subjectivity. However, reviewers’ attributes are varying from E-commerce platform to another according to information provided in reviewer profile platform.

The most common reviewer’s attributes that affect RH will be listed as the following. First, (Siering, Muntermann, & Rajagopalan, 2018) investigated the impact of reviewer-related attributes such as reviewer expertise and reviewer non-anonymity on review helpfulness. Furthermore, they considered other control variables include Review depth, review readability, and review extremity as content-related attributes. (Hong, Xu, Wang, & Fan, 2017) classified the attributes of review into two groups one of them is Reviewer-related factors such as (Reviewer information disclosure, Reviewer expertise, Reviewer expert label, Number of reviewer friends and fans). On other hand, (Barbosa, Moura, & Santos, 2016) hypothesized that there are two important attributes influence RH. These attributes are based on the authorship attributes include Author Reputation such as (Average number of reviews votes, Average number of positive votes, Number of friends a user has in the Steam community). Author Expertise attributes contains number of hours a review author played the analyzed game.

Finally, (Karimi & Wang, 2017) analyzed the impact of reviewer image on RH. They hypothesized that "if reviewer profile im ge available, it has a positive effect on RH". Besides, they suggest that it may interact with review attributes such as review length, rating valence, and review equivocality to resulting stronger effect on RH. However, many techniques of RH prediction are used in the literature. First, the experiment in (Salehan & Kim, 2016) used some regression equations to prove the correlation between these attributes and RH. On the other hand, the researcher in (Barbosa et al., 2016) used ANN MLP for prediction and the Correlation-based Feature Selection (CFS) to validation. While the experiment in (Zhang & Zhang, 2014) produced the predictive model by the SVM, one of the top supervised machine learning algorithms. They applied the algorithms by using song WEKA tool (Eibe Frank, 2016). Also, The researchers in (Ngo-Ye & Sinha, 2014) designed a text regression test to predict review helpfulness by using support vector regression (SVR). And the experiment in (Ahmed et al., 2017) implemented using SVM algorithm for sentiment analysis with two different kernels: Poly Kernel and RBF Kernel.

Another research in (Goswami, Park, & Song, 2017) experimented various combinations of the attributes that affect the RH with the neural network algorithm. Also, Authors repeated the experiment with different algorithms such as MLP and Naïve Bayes. Another study (Karimi & Wang, 2017) applied regression and descriptive statistics, including mean and standard deviation for all variables and their Pearson correlation coefficients. In addition, the study (Ghose & Ipeirotis, 2011) decided to use two approaches regression and classification approach to build a binary prediction model that classifies a review as helpful or not. They did the classification experiment with Support Vector Machines and Random Forests. Finally in (Siering et al., 2018) the researcher applied a Tobit regression analysis to observe the impact of different attributes on RH.

Consequently, the all best ways that mention above is used in outspread studies and there is lack for one study merge all this respectable work in RH with few research gaps are found in these researches. First, there are lack of comprehensive model to control all stage of RH on Review-based platform. Previous researches in the field of RH are based on direct experiment which is missing of appropriate techniques of data collection and data pre-possessing for each platform. Second, there is an important research gap regards to the algorithms used in RH. The choosing of algorithms of RH experiments is still focus on regression only with few studies approaching classification or prediction. Thus, different algorithms need to apply in same dataset to verify the best fit algorithm in this kind of studies. In order to reduce these research gaps discussed above, this research is interested to discover a new approach to perform a good RH experiment. A novel model is proposed in this research in continuation of filling these gaps as showed in next section.

Inclusive Review Helpfulness Model (IRHM)

Various experiments have done to analyze RH in different platforms. However, there is still a gap in literature of build skilled classifier use most important attributes to predict RH on any E-commerce platform. Therefore, to bridge this gap and accomplish the objectives of this research, a novel model has been suggested. It targets to deliver an inclusive review helpfulness model (IRHM) that control all stages of RH completely. IRHM extracts the most important attributes influence the helpfulness of online reviews. More precisely, the reviews that may gain consumers attention to judge it as helpful can be allocated through some attributes of this review. Investigating of what make the review helpful in E-commerce platforms require an exploration of what are the attributes involve on this review that make the customer consider it helpful.

Additional task besides determining the most important attributes affecting RH is to analyze the polarity of review text itself. For example, some customers trust the review if it is neutral and shows intermediate of positive and negative opinion about a particular product. Second goal of the IRHM is to build a skilled classifier that can predict the RH on any platform that may not have helpful button based on the trained dataset. This goal can help customers in case of lacking helpful button. The overall design of IRHM contains three major phases as shown in Figure 1:

1. **Data collection phase**: Extracting reviews and other reviewer's features from E-commerce websites.

2. **Pre-processing phase:** After collecting the required data, a lot of preprocessing techniques are applied to prepare data for the next phase.

3. **Processing phase:** This phase identifies the most important attributes and use it in classification and prediction of RH to obtaining the performance of the IRHM.

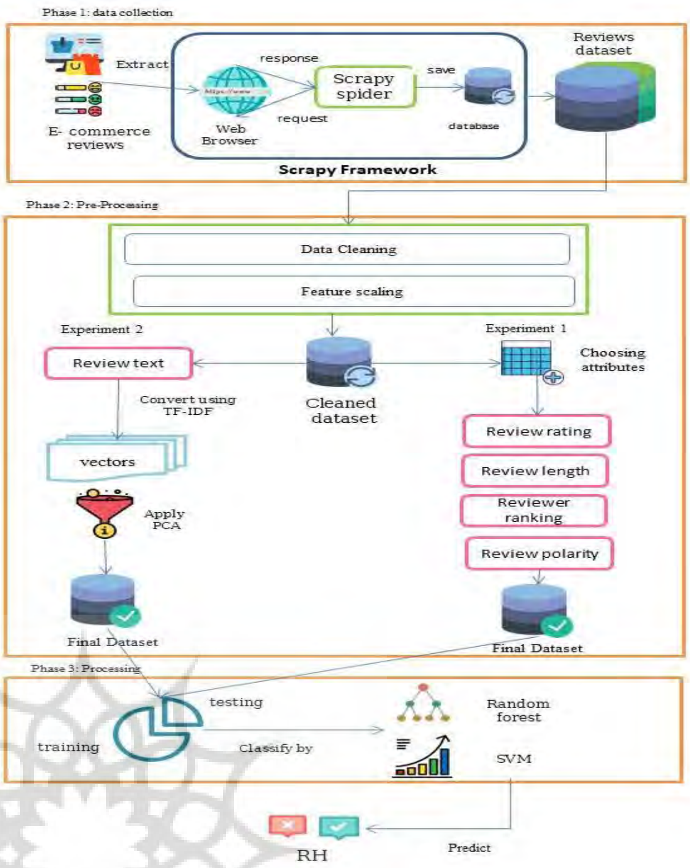

Figure1. IRHM Basic Block

IRHM implementation

Amazon.com was chosen to extract data required for IRHM implementation due to its massive amount of reviews and reviewers' attributes. Next subsections illustrate the details of IRHM implementation.

Data collection

The focus on this research was on products that had more than 2500 reviews. While the examined product types were electronics, books and Home &kitchen. The downloading of reviews and reviewer insights for every product has done by using SCRAPY framework & Selenium (Myers & McGuffee, 2015). Hence, once the IRHM triggered the framework, the crawler runs through all the reviews and collects information through SCRAPY with parallelly opens the user's profile page through Selenium headless chrome browser to captures user insights data, appends and produces the final output row on CSV file.

The final collected dataset consisted of 9127 raw reviews include three products: RedmiNote5 from Electronics, Lifelong mixer from Home & Kitchen and Rich dad Poor dad from Books. Choosing these categories have made to keep a diversity in review and reviewers base. Also, the focus was on bestselling products that had greater than 2500 reviews to analyze quite large review samples. The final dataset involves 13 raw attributes include: Review_helpful_count, Pictures_count, Review_comments_count, Reviewer_ranking, Reviewer_helpful_votes, Review rating, Reviewer_review_count, Review_badge, Review_id, Review_date, Review_title, Review_text and Reviewer_name. Table 1 and Table 2 summarize all data collection process and attributes' description.

Table 1. Raw Datasets

Category	Product	Number of reviews
Electronics	RedmiNote5	2868
Books	Rich dad Poor dad	2617
Home & Kitchen	Lifelong Mixer	3642
Total	9127	

Table 2. Attributes collected

Attribute Name	Discerption
Review_helpful_count	Number of people that vote helpful to review.
Pictures_count	Number of pictures the review has.
Review_comments_count	Number of comments on the review.
Reviewer_ranking	Rank of the reviewer measured by the logarithm of the Amazon Rank.
Reviewer_helpful_votes	Number of votes that review have.
Review_rating	The rating given in this review from 1-5.
Reviewer_review_count	Number of reviews written by reviewer.
Review_badge	Verified Purchase or not.
Review_id	The ID of review given by amazon.
Review_date	Date of review post.
Review_title	Number of words in title text.
Review_text	Number of words in review text and to get the polarity of the review.
Reviewer_name	The name of reviewer.

Data Pre-processing

In IRHM, the preprocessing phase contains five main steps: Data Cleaning, Feature scaling, Sentiment analysis, Term Frequency–Inverse Document Frequency (TF-IDF) and Principle Component Analysis (PCA). First, the dataset is cleaned and prepared for classification by applying the following:

1. The row data has Reviwer_ranking attribute which is string data type as following formula: "232,343", so it should be converted to integer in order to avoid read it as

string in compiling process. This step is done by using regular expression concept in programming.

2. Some review contains non-meaningful spaces and enters between review sentences which will affect the attribute Review_length calculation. In addition, many of reviews text has comma between sentences typed by the reviewers that may be considered as another attribute in CSV files. Therefore, all these spaces, enters and commas are removed by using same regular expression concept.

3. Reviews that have small total votes are useless for customers. For example, a review having 4 helpful out of 5 total votes is not expected to be valuable than a review having 44 helpful out of 55 total votes for example. Hence, IRHM eliminates the reviews that have at least 5 total votes to ensure robustness of the model (Krishnamoorthy, 2015). This task was done manually by sorting the attributes ascending then remove the tuples that have less than 5 total votes.

4. IRHM also removes missing values (i.e. no textual content) with total votes are likely to be fake review.

Then, The IRHM uses standard scaler to normalize the data with mean equal to zero and standard deviation equal to one. The adopt of standardization in the IRHM is because it has correlation and measures of association. Also, it is useful for managing the size of attributes in an iterative procedure to prevent numerical instabilities due to large datasets (Esmailian, 2019). As a result, the dataset was put in normal distribution.

In addition, Sentiments analysis in IRHM is done by text blob package (Loria, 2018) on review text attribute in order to investigate the impact of the polarity on RH. The Naïve Bayes Classifier has trained on reviews text to assign a polarity to every sentence in the text. output values of text polarity and the sentiment classification was added as new attributes to the dataset.

Moreover, IRHM uses the TF-IDF to test the impact of sentiment analysis of review text on RH, this step is done by convert the 'Review_Text" into vectors and extract features from it automatically. Then, eliminate the features that are generated by the 'Review_Text' vectorization by using PCA.

After the pre-processing phase has finished, datasets are ready to be processing by applying Logistic regression (LR), Support vector machine (SVM) and Random forest (RF) algorithms to build a predictive model. The RH will classify using the existing voting system at amazon by extracting the RH of every review and adding it as independent attribute on the dataset. In addition, The LR algorithm is used to show the important attributes affecting the

RH before use it as dependent variables in the predictive classifier. Table 3 shows significant attributes coefficients for the IRHM.

Table 3. Logistic Regression Coefficient Result

Variable	Coefficient
Review_rating	-0.33
Review_length	0.62
Reviewer_ranking	-0.20
Review_badge	0.96
Pictures_count	0.37
Review_polarity	-0.18

Then, The IRHM uses these significant attributes to build predictive classifier of RH by using SVM and RF. The first experiment uses Nonlinear kernel Radial Basis Function (RBF) of SVM due to the multi-dimensional nature of the dataset. Then, IRHM tries another experiment use the 'Review _text' only as input of the classifier after applying TF-IDF with PCA to examine the unique impact of the 'Review_text' on RH. SVM algorithm use as first trial then its repeated with the RF algorithm to ensure the best quality of the classifier and the performance measures was calculate and presents in next section.

IRHM Performance

The performance of IRHM was evaluated by calculating the performance measure such as (Accuracy, Precision, Recall, F-measure) to ensure the performance and fit the IRHM in the context of RH researches. Also, Receiver Operating Characteristic (ROC) with its Area Under Curve (AUC) was calculated to ensure model skillful. Table 4 illustrates these measures of IRHM classifiers. In general, the accuracy of SVM in first experiment is 89% while the accuracy of the RF and SVM in second experiment are approximately similar and around 93-94%. On the other hand, the precision of the SVM in first experiment is better than the SVM and RF in second one, 0.75 precision in first experiment compared with 0.32 and 0.67 in second experiment. While the Recall are almost the same in SVM and RF and around 0.20.

Table 4. Performance measures of IRHM

Metrics	First experiment	Second experiment	
	SVM	SVM	RF
Accuracy	89%	93%	94%
Recall	0.20	0.11	0.20
Precision	0.75	0.32	0.67
F-measure	0.32	0.16	0.31

Moreover, the AUC in ROC curve is used as extra evaluation method to ensure the performance of IRHM where it reflects the classifier rank by address if randomly chosen positive instance are higher than randomly chosen negative one. The AUC results of IRHM first experiment is 0.82 while it increased significantly in the second experiment to 0.85 in SVM and 0.94 in RF General rules defined by (Hosmer, Lemeshow, & Sturdivant, 2000) were keep to classify the evaluation performance by defining AUC as: “excellent” if AUC ≥ 0.9, “good” if 0.9 > AUC ≥ 0.8, “fair” if 0.8 > AUC ≥ 0.7, “poor” if 0.7 .

Therefore, IRHM performance classifies "good" in SVM at two experiments and "excellent" in RF according to (Hosmer et al., 2000). Figure 2 and 3 show the ROC curve with AUC of IRHM model.

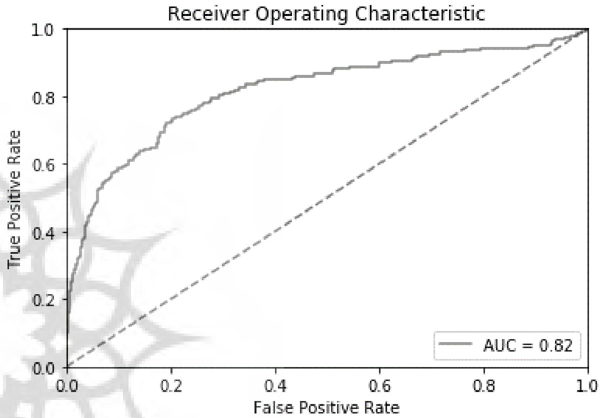

Figure 2. ROC and AUC of IRHM First Experiment

(A): ROC for RF (B): ROC for SVM

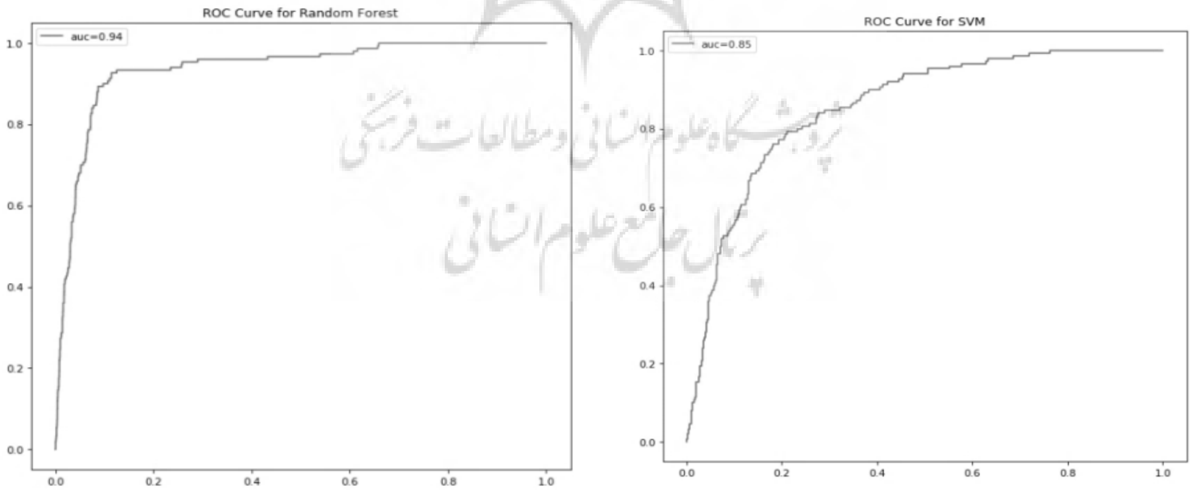

Figure 3. ROC and AUC for Second Experiments in IRHM

Discussion

The IRHM achieves high-quality results on LR, SVM and RF compared with other models use the same attributes and algorithm. First, for regression coefficient IRHM will be compared with four related researches (Salehan & Kim, 2016), (Wu, 2017), (Ghose &

Ipeirotis, 2011). These researches used to compare LR coefficient as initial exploration of the most important attributes affect the RH. For example, the Rating attribute in Wu (Wu, 2017) was -0.242 while it is -0.33 in IRHM with nearly 0.1 increased in IRHM. This means that if the Rating decreases, the RH will increase due to a negative sign.

The second attribute observed was Review_length, its titled Review_Depth in Wu (Wu, 2017) and its coefficient was 0.747 besides 0.407 in Salehan (Salehan & Kim, 2016) while its coefficient in IRHM is 0.62. It was generating a suitable coefficient between two values in previous researches. So, the coefficient demonstrates if the Review_length is increased the RH will increase too.

Then, Review_polarity attribute was examined in Salehan (Salehan & Kim, 2016), it has a coefficient equal to -0.068 while it -0.18 in IRHM that consider good enhancement with a small negative impact on RH. Forth attribute observed was Review_badge that named Credibility in Wu (Wu, 2017). The Credibility coefficient was 0.522 compared with 0.96 in IRHM. Review_badge reflects if the reviewer is verified purchase or not that means the review is definitely coming from an actual experiment, this explains the highest and positive impact of RH.

The last attribute that was compared in IRHM is Reviewer_Ranking, it was bringing 0.258 in (Hong et al., 2017) while it's approximately -0.20 in IRHM. It has almost the same coefficient but with a negative impact. That means if the Reviewer_Ranking increases the RH will decreases, which reflects the nature of the Amazon ranking system (the small ranking number is the highest level than the large ranking number). Table 5 summarizes all the coefficient between IRHM and other models.

Table 5. IRHM validation (Benchmark of LR)

Reference	Comparative model		IRHM	
	Attribute	**Coefficient**	**Attribute**	**Coefficient**
(Salehan & Kim, 2016)	Review Length	0.407	Review Length	0.62
	Review sentiment	-0.068	Review Polarity	-0.18
(Wu, 2017)	Review Depth	0.747	Review Length	0.62
	Rating	-0.242	Rating	-0.33
	Credibility	0.522	Review badge	0.54
(Hong et al., 2017)	Reviewers Expertise	0.258	Reviewer Ranking	-0.20
	Review depth	0.114	Review Length	0.62
(Ghose & Ipeirotis, 2011)	Rating	-0.320	Rating	-0.33

On another hand, to validate the IRHM results and put IRHM in context of RH classification, the benchmark and comparison step was done with other scientific experiment which uses similar attributes and algorithms. the trial with SVM in IRHM model produce excellent accuracy comparing with scientific study in Ghose (Ghose & Ipeirotis, 2011) and Krishnamoorthy (Krishnamoorthy, 2015) where they are 87.68% and 84.84% consecutively against 89% in IRHM model. Though, the accuracy of SVM and RF in the second experiment are better than the first experiment with approximately a similar value 93-94% Table 6 and Figure 4 show these results.

Table 6. IRHM Performance Against Other Models

Reference	Classifier	Comparative Model Accuracy	IRHM first Experiment	IRHM second Experiment	
				SVM	RF
(Ghose & Ipeirotis, 2011)	SVM	87.68%	88%	93%	94%
(Krishnamoorthy, 2015)	SVM	84.84%			

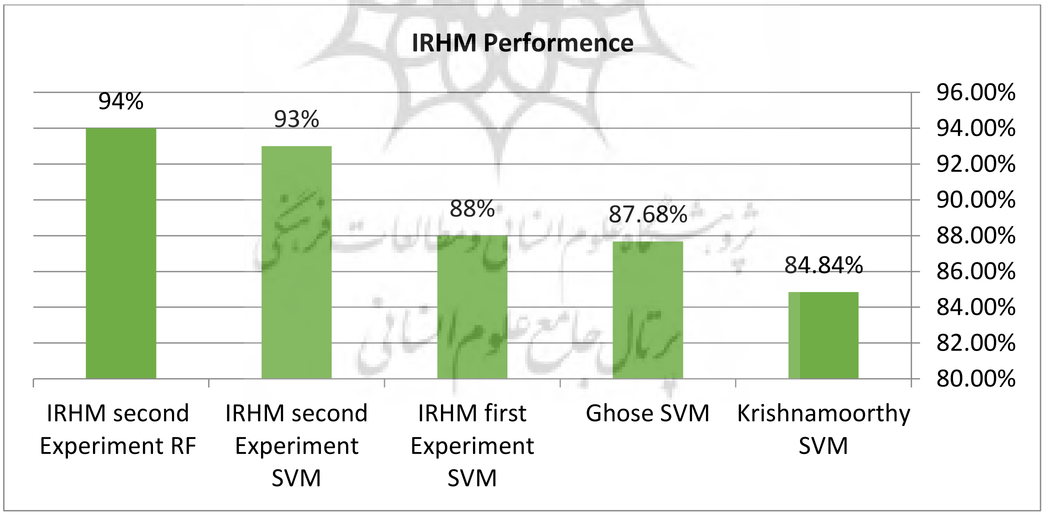

Figure 4. IRHM Performance Benchmark

Conclusion

This research paper offered a complete effort in the field of Review Helpfulness, which aims to deliver a suitable model of RH classification called IRHM. IRHM is used to improve the existing experiments performance and existing algorithms by using its three phases: Data collection, pre-processing and processing phase. The model was bringing good performance against similar ones used same attributes and algorithms. It outperformed as skillful model with 94% accuracy.

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