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An Enhanced Web Mining Approach for Product Usability Evaluation in Feature Fatigue Analysis using LDA Model and Association Rule Mining with Fruit Fly Algorithm

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Abstract

Objectives: The rapid growth of E-commerce emphasizes the customers' attention on product purchases through large number of websites. The customers tend to buy the products with more and best features, but those features fails to satisfy their expectations. This limitation is termed as Feature Fatigue (FF) in product usability analysis in web mining. The objective of this novel approach is to evaluate the product usability effectively and supports the designers to make decisions in future. **Methods:** The consumers' reviews are collected from various E-commerce websites using web crawler. These review sentences are preprocessed by removing the stop words and stemming. The synonym dictionary is created from the preprocessed sentences. **Findings:** In order to attain usability evaluation frequent item set is identified by improved Apriori algorithm and the association rule is generated. Finally the product capability is evaluated effectively in the FF analysis using analyzed features. **Improvements:** The product reviews are gathered from the E-commerce websites to analyze the feature usability of that product and obtain 95% accuracy. The feature analysis report helps the manufacture to alleviate the FF by balancing the capability and usability of the product.

Keywords: Association Rule Mining, Feature Extraction, Feature Fatigue, Usability Analysis

1. Introduction

Online shopping is now more popular, due to the rapid growth of Internet usage worldwide. With the immense development of E-commerce the amount of customers in buying online products is also increasing day by day. Once the customers decide to do online shopping, they refer the reviews about the products posted by other customers. Usually, after purchasing the products, the customer's posts their own opinions about the products in Social websites and blogs such as Facebook, Twitter, Amazon[1] etc. In general, reviews are collected from two sources one is from the Sellers' website with descriptions from review platform and the second source is from the Customers' site or blog[2]. The reviews collected may either positive or negative based on the features of the product and the service provided.

Based on those reviews, the reputation of the product and the organization may increase or decrease. The reviews of the customers help other customers to make decisions in buying the products, as a word-of-mouth[3]. The goodwill of the organization is ruined by the negative reviews. Moreover, most of the negative reviews illustrate the dissatisfaction of the customers on the product features after using it. This dissatisfactory of the customers on product usability is defined as Feature Fatigue[4].

To study the Feature Fatigue analysis, the product usability analysis is required. The three aspects of the usability are Efficiency, Effectiveness and User satisfaction[5]. Based on the testing methods[6] and the survey data[7]

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the traditional methods evaluate the usability of products. This mechanism is a time consuming process and its economics cost is high. In order to reduce cost and time, this paper proposed a novel framework which focuses on product usability analysis based on web mining[8].

The novel approach proposed in this article uses various customer reviews which are collected from web. The proposed approach consists of three phases. The first phase includes the data preparation process and the second phase is Usability Analysis and the third phase is Feature Fatigue Analysis. At the beginning stage the input i.e. customer review is raw review, so it is preprocessed[2] to obtain a review sentence which is the input for Association Rule mining process[9]. The NLP is used for POS tagging and then the synonym dictionary is developed by LDA[10] and Synonym Lexicon[11] method. The candidate feature set that is the synonym dictionary is created by identifying the nouns phrases from the POS tagging with LDA, which extends the Synonym Lexicon. Then filtering rules are applied to the extracted feature set to obtain the final product feature.

The Fruit Fly Association Rule Mining[12,13] is used in this work to decide the semantic orientation of the review sentence to obtain and the frequent item set is obtain using the improved Apriori algorithm. The usability evaluation and the product capability is evaluated in the FF Analysis, with these evaluation FF degree is measured which is used to alleviate FF effectively.

2. Related Works

Natural language processing is research process which is related to human-computer interaction area. The proposed framework focus on usability analysis which is needed to work on Natural languages, as the customers posts their reviews in a simple speech language[13]. This section describes some related work that uses the NLP or LDA to process the natural languages and also some related works are described for mining the opinion and Feature Fatigue analysis from the customer reviews.

In[14] a novel grouping idea is proposed for product features. The Latent Dirichlet Allocation (LDA) is used by the author to extract large scale constraints. The topic modeling method LDA is enhanced to handle must-links constraints and the cannot-links constraint to extract the feature automatically. Then result of the constraint LDA is then applied to the extracted feature to group the product feature.

In[15] a method to extract the opinion features from two different corpora is presented. Domain-specific domain-independent are the two corpuses used in this work. The author takes the hotel and cellphone reviews and generate a set of rule to extract the candidate opinion feature from the domain-specific corpus. Its Domain Relevance (IDR) and Extrinsic-Domain Relevance (EDR) scores are estimated. The author confirmed from the extracted feature, that it has less EDR scores and more IDR values

In[16] a Feature Fatigue Multi-Objective Genetic algorithm method is introduced to solve the product usability problem during the product designing stage. The fitness function represents the uncertain customer preferences and their relationship based on Bayesian network. This approach provides many solutions along the Pareto-optimal frontier but it has less focus on what kind of feature should be included to alleviating Feature Fatigue.

In[17] an efficient algorithm based on finite state machine was developed to remove the stop words in Arabic language. A set of 242 Arabic abstracts and another dataset is extracted from the Saudi Arabian National Computer Conferences (SANCC) and another set of data chosen from the holy Q'uran. The novel framework verifies the combination of data to achieve minimum time utilization but it has its limitation in accessing the dictionary. This approach for stop word removal provides approximately 98% impressive result.

In[18] a novel approach for Feature Fatigue analysis were proposed based on behavioral decision making theory. By analyzing the customer review the author describes that the customer purchase decision is varying before buying and after using the product. This leads to the customer dissatisfaction and their purchasing opinion is changed. This novel approach adopts six dimensional value models that append the features on customer perceived value before and after use. A further analysis model is applied for analyzing FF.

In[19] a syntactic approach for opinion mining was proposed. This approach used an aggregate score, SentiWordNet, syntactic dependency and aspect table of opinion words. The author applied his work on restaurant review and made a comparison with POS tagger method. The accuracy of the annotated test set result is 78.04% which is 6% more than existing method which uses POS for feature extraction. This paper uses the POS tagger for feature extraction along with LDA and Synonym Lexicon, therefore the proposed work provides an impressive result.

In[20] made an investigation to identify importance of product usability by comparing other attributes. The active information search method is applied initially to identify possible attributes. The author takes the mobile phone as the example product. Structured preference elicitation and ranking are proposed to interview and find the important attributes. A conclusion is made in terms of product choice, usability is indeed important but not as much as users believe and the other important attributes are cost, features and aesthetics.

In[21] made a research based on statistical regression and correlation analysis with Multiple Linear Objective Programming (MLOP) for obtaining sensibility words. The determination can be made to analyze perceived feeling of consumer about that particular product with this analysis. The word is verified whether it is related to the product design or not. If the words had some relationship then optimal design criteria is derived to attain maximum possible perceived quality of system. This research is conducted by taking thirteen sensibility words, twelve product models with forty nine design elements. And the final result is analyzed using fuzzy set logic and MLOP.

In[22] performed an investigation on dimensionality reduction using Singular Value Decomposition (SVD), stop-lists application and word stemming for improving the performance and also proposed a semantic task which is applicable to work with larger corpus. An improved SVD based method is applied for generating semantic representation.

Various authors proposed different natural language processing approaches and they are explained above. Kano's model[23], Bass model[24] and Norton-Bass model[25] are the various proposed approaches existing for Feature Fatigue analysis. Moreover, the existing approaches for Feature Fatigue analysis are also discussed. Though different approaches exist they have certain limitations and to overcome that the work proposes NLP tool along with LDA to generated better accurate results. FF is analyzed by rule mining from the synonym dictionary and FF degree is evaluated for better analysis of product features and they are discussed in the following section.

3. Proposed Methodology

To evaluate the product feature effectively, a novel method has been proposed. By determining a feature, which should be included with the product to alleviate the FF. To implement, the method is proposed through 3 phases namely, 1) Data Preparation, 2) Product Usability Analysis and 3) Feature Fatigue Analysis. Figure 1 shows the framework of the proposed methodology.

During phase 1, the concept of data preparation involves collection of reviews, preprocessing procedure and creation of synonym dictionary. In the second phase, association rule mining with fruit fly algorithm and improved Apriori algorithm is applied to analyze product usability. In the final phase, FF analysis is performed. This ensures that the product feature will be evaluated effectively and supports decision making for the product designers in future. In the following subsections, the methods of three phases are discussed.

3.1 Phase 1 – Data Preparation

This phase consists of three processes: Collection of reviews, preprocessing procedure and creation of synonym dictionary.

The process of review collection is made to collect the reviews from web about the product. Those collected reviews are then processed to be converted as sentences. Hence, it is to be used by association rule mining, the reviews are converted as sentences through which the synonym dictionary is created.

In the preprocessing process, the collected raw reviews are preprocessed to generate review sentences, which is stored in review collection database. The review evaluation is processed only on sentences. Hence the raw reviews are preprocessed and converted into sentences which are then used by association rule. The stop words are identified and cleared in the data cleaning process as suggested in[26] which refers to the most common words in speech language (English) are removed and also the

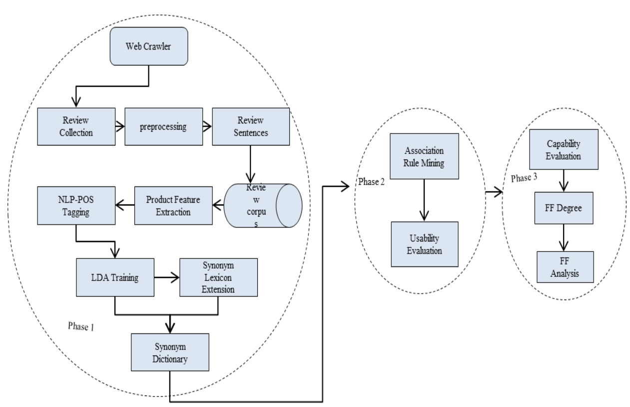

Figure 1. Framework of proposed methodology.

function words[27] which contain the ambiguous meaning or little lexical meaning are also removed.

The function words express the grammatical relationship between the words or in other terms the function words might be conjunctions, prepositions, articles, pronouns. This research work focus on extracting the relevant words that has the proper meaning about the product usability. In this case the functions words are not needed so it is removed and the context words are generated.

The context words refer to noun, verb, etc. After the context words generated, stemming[28] is applied on it. Stemming is one of the important processes in information retrieval. This is applied to extract the common words. For example "wonder, wonderful, wondering, is considered as the input for stemming process, the output will be "wonder" likewise the stemming process removes the letter which is ending with s, ed, ing, ly.

3.1.1 Synonym Dictionary with LDA and Lexican Algorithm

Customer posts their opinion on their own words in the review and they use different words to mention the same feature. For example 'photos, images, pictures 'mention the same feature for the camera product. Collecting the synonyms from this kind of feature is difficult process. A Natural Language Processing (NLP) is applied for Part of Speech (POS) tagging. NLP parse each and every review sentence and produce a Part Of Speech tag, such as noun, verb, etc. The POS tagging provides the initial feature from the extracted nouns. These features are further processed by the LDA model and generate the final product feature.

The synonym dictionary is developed by Latent Dirichlet Allocation (LDA) and Lexican algorithm from the extracted nouns. The working procedure of the synonym dictionary creation process is explained in the Figure 2.

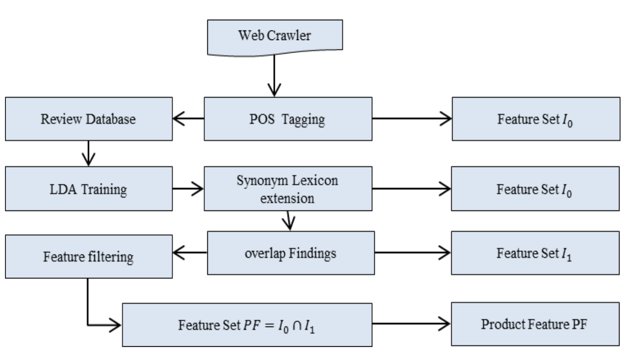

Figure 2. Procedure of synonym dictionary creation.

3.1.2 LDA Model

The LDA considers a single document as a mixture of several topics. The proposed work process with many document such as Processor review as one document and RAM capacity review as another document and so on. The processor, Ram, WI-FI types, Battery is considered in LDA model and it starts to execute by sampling a word distribution from a prior Dirichlet distribution. In the synonym lexicon extension process, an extension is performed from the original feature F_1 to F_2 by appending the synonym of F_1 Finally a new feature set is created by intersecting $F_0 \cap F_2$. The collection of new feature is the synonym dictionary.

The Figure 3 explains LDA and Lexicon Synonym process for synonym dictionary creation. In Phase 1, the data preparation and synonym dictionary creation is performed with the help of NLP and Synonym Lexicon Algorithm. The following section describes the second phase of this paper.

3.2 Phase 2: Product Usability – Improved Association Rule Mining and Fruit Fly (ARMF)

The association rule mining[29,30] is an important task in data mining and it is used to find the frequent pattern, correlations and associations in the information repositories.

D_i: Document in review corpus D
μ_i : Topic distribution of D_i
Dt: Dirichlet distribution
α, β: Parameters of Dirichlet prior
ϑ_k: Word distribution of topic k
$W_{i,j}$: word
$t_{i,j}$: topic of j_{th} word in D_i
Begin
    For each D_i:
        Select $\mu_i \sim Dt(\alpha)$
        Select $\vartheta_k \sim Dt(\beta)$
    End for
    For each word W_{ij}:
        Select topic $t_{ij} \sim \text{Multinomial}(\mu_i)$
        Select a specific word $W_{ij} \sim \text{Multinomial}\left(\vartheta_{t_{i,j}}\right)$
    End for
    For each word W_i in F_1
        For each syn or near-syn in synonym lexicon
        Assign $D = syn_i$ if $syn_i \nexists D$

Figure 3. Algorithm for LDA model.

Usually the association rule mining is used to find the frequent pattern, correlations and associations in the information repositories. Similarly in the proposed work, the rule mining is applied to mining rule to check whether the generated review sentence is related to the features usability or not.

The state of the problem for mining the association rule is as follows:

$$ls = \{ls_1, ls_2, ls_3, \ldots, ls_n\}$$

Set of items where *ls* is the itemset. And the set of transaction is:

$$Trans = \{T_1, T_2, T_3, \ldots, T_n\}$$

Each Trans contains the items of the *ls*. Association rule is in the form of $p \rightarrow q$. p and q is the item in the ls and $p \subset ls$, $q \subset ls$ and $p \cap q$. When p was in transaction then q is almost involved in the transaction too.

3.2.1 Frequent Itemset

An itemset is said to frequent, whenever its support is greater than or equal to minimum support threshold. In this work some of the itemsets are processor, battery, memory, display feature, Wi-Fi type, RAM, etc. and the items are "good", "clear", "simple", "better", "worst", "nice", etc. The set of items with high support is applied to find the association rule. The support for a rule is defined by its transaction percentage which has $p \cup q$ and it describe the show frequent, the rule is used in the transaction T. The following formula represents the support of a rule:

$$Support(p \rightarrow q) = \frac{p \cup q}{N}$$

$p \cup q$ Represents the number of transaction of all items of the rule and N refers the total transaction. The above support formula calculates the relative support value. The confidence is defined by its transaction percentage having p that also contains q.

$$C(p \Rightarrow q) = R(q|p) = \frac{support(p \rightarrow q)}{support(p)}$$

Confidence value is an important measure that views all transaction that contains certain item defined by the rule. The precision, recall and f-measure is calculated with their respective formulas and are discussed in Section 4. And the usability evaluation operation is performed in the following section.

3.2.2 Apriori Algorithm

Apriori algorithm[31,32] is utilized for frequent item set mining and association rule learning on transactional databases. This is achieved by identifying the frequent individual items in the database and then it is extended to larger item sets until it appear sufficiently often in the database. The association rules can be determined by these frequent item sets which highlight general trends in the database.

3.2.3 Limitation of Apriori

The main limitation of Apriori is the cost and execution time is high[32, 33]. For example, to detect frequent pattern in size 100 (r1, r2… r100) then 2100 candidate itemsets have to generate which is costly and takes more time in candidate generation. Therefore it scan database many times repeatedly for finding candidate itemsets. The Apriori for finding frequent set is very poor in efficiency when there is large number of transactions.

3.2.4 Improved Apriori Algorithm

The improved Apriori algorithm[33,34] decrease the number of candidate items in the candidate item set C_j. In the Apriori algorithm1, C_j - is compared with support level, once it was found. If the itemsets are less than the support level then it is pruned and the itemset. L_k-1 is produced which is connected with itself and lead to C. In the improved algorithm, before the generation of candidate item sets C_j the prune method count the times of all items occurred in L_k-1 and delete item sets less than k-1 in L_k-1. In this way, the number of connecting items sets will decrease so that the number of candidate items is reduced. In the proposed approach the Apriori is applied to obtain the frequent itemset of customer review sentences. A set of sentences $S_i = (w_1, w_2, \ldots w_n)$, where w is the words in S. The frequent set of S_i is obtained by the following Apriori procedure. The Figure 4 shows the Apriori algorithm.

3.2.5 Rule Set Reduction

The generated association rules are extremely large. Therefore it is important to prune the rules to make the classifier more effective and efficient. The Fruit fly Optimization Algorithm (FOA)[34] has the potential to solve the difficult optimization problem. The FOA is based on the characteristic of fruit fly to find the optimal solution. Combination of Fruit Fly Optimization Algorithm (FOA) and improved Association Rule Mining is applied in the

Algorithm

S_i: set of sentences

f_i: Frequent Item set

C_j: Candidates generated from f_i

T: Database

Min_sup: minimum support

Begin

$f_1 = Frequent\_1 - itemset(d)$

For (j=2; $f_{i-1} \neq \emptyset$; ++)

Prune I(f_i);

$C_j = apriori\_gen(f_i; Min\_sup)$

For all sentence s ∈ d

Find the subset to all C=subset (C_k, s)

For each candidate c ∈ C_s

c.count ++

$f_i = \{c \in C_j \mid c.count \geq \min\_sup\}$

Return$U_i f_i$

Figure 4. Aprori algorithm.

Fsl: Fruit fly swarm location

Rv: Random value

Dt: Distance to origin

S: Approximate value of Smell concentration

Smell_i: Smell concentration value

Fitness_fn: smell concentration judge function

Begin

Randomly initialize Fsl as

$$X_i = X\_axis + Rv$$

$$Y_i = Y_{axis} + Rv$$

do

If (food position= unknown)

Find Dt and S

$$Dt_i = \sqrt{X_i^{\,2} + Y_i^{\,2}}$$

$$S_i = \frac{1}{Dt_i}$$

End if

Substitute S into fitness_fn

$$\text{Smell}_i = \text{fitness\_fn}(S_i)$$

While ($\text{Smell}_{i-1} > \text{Smell}_i$)

Figure 5. FOA algorithm.

proposed work for mining the exact Product Feature Usability. In the data Preparation module, the NLP is used just for synonym dictionary creation. The dictionary contains so many features about the product. The required feature is mined from these features by ARMF.

The Fruit fly Optimization Technique is based on the food searching behavior of the fruit fly. They are very sharp in sensing osphresis and vision. The fruit flies have this nature because of its osphresis organs; with this it can able to find the food location from 40 Km away[12]. This fruit fly concept is applied in the proposed work to obtain the required product feature from the dictionary. The parameters in the dictionary are considered as the initial position of the fruit fly operation and it described as InitX_axis and InitY_axis. Set of association rules are pruned by following Figure 5.

3.2.6 Usability Evaluation

Usability is important aspect especially in mobile application and web application. After the rule mining it is simple to add the rules to the new review sentence. It selects the rule which can match the sentences. Based on the confidence and support the classifier found a rule to match the sentence. The Figure 6 shows the usability evaluation summary.

The product designers should notice the usability of that product; otherwise user will leave that application/product. The usability of the product is evaluated and its result is shown in Section 4.

The association rule mining with Fruit fly Optimization Algorithm is obtained in this phase and with that rule usability evaluation is measured which is represented in the Table 1. The capability measure is calculated in the third phase by having both usability evaluation and the capability evaluation and the feature fatigue analysis is applied in third phase.

3.2.7 Phase 3 – FF Analysis

Customers need to buy the product with more feature but they dissatisfy with the product if their feature is not fulfilling their expectations. This problem is known as

Product - Samsung Laptop

Feature 1 – Battery
PU –
< Review Sentence 1>
<Review Sentence 2>
....
<Review Sentence n>
NU –
< Review Sentence 1>
<Review Sentence 2>
....
<Review Sentence n>

Feature 2 – Processor
PU –
< Review Sentence 1>
<Review Sentence 2>
....
<Review Sentence n>
NU –
< Review Sentence 1>
<Review Sentence 2>
...
<Review Sentence n>

Feature 3 - Memory
....

Figure 6. Usability evaluation summary.

Table 1. Usability evaluation

Score	Description
9	Strong negative impact
7	Weak negative impact
5	Not apparent impact
3	Weak positive impact
1	Strong positive impact
8	Weak negative impact
6	Weak negative impact
4	Weak positive impact
2	Strong positive impact

product usability problem/Feature Fatigue (FF)[35]. This FF dissatisfied the customers so this research work focused on alleviate FF before that an analysis of FF is made with the usability evaluation and capability evaluation.

3.2.8 Capability Evaluation

The two important factors are the Usability Evaluation and the Capability Evaluation. While purchasing the products such as cellphones, laptops, etc users always selects the high feature products, even though they know that more features will lead to usability problem. After using that product then customer realize that usability is more important. The capability of the product is evaluated to analyze FF. The capability evaluation result is shown in Table 2.

3.2.9 FF Degree

The evaluation of Usability and Capability is applied to find the degree of FF. The FF degree calculated by the following formula:

$$\text{FF Degree} = \text{UE} - \text{UC}$$

UE and UC are normalized score of Usability and Capability:

$$UE = \frac{FUE - FUE_{min}}{FUE_{max} - FUE_{min}}$$

$$UC = \frac{FCE - FCE_{min}}{FCE_{max} - FCE_{min}}$$

FUE represents the Feature Usability Evaluation and FCE represents the Feature Capability Evaluation. FUE and FCE scores are obtained according to Tables 1 and 2.

The Capability Evaluation is obtained in this phase. The data preparation, product usability analysis and Feature Fatigue analysis is performed in the proposed methodology. Different features with various strategies

Table 2. Capability evaluation

Feature	Synonym
Processor	CPU, machine, company, prepares.
Speed	move quickly, hurry, race, run, sprint, dash.
Cache	Hoard, store, stockpile, stock, supply, collection.
Memory	Recollection, remembrance, reminiscence, evocation.
RAM	Force, thrust, plunge, stab, push, sink, dig, stick, cram.
Display Features	Exhibit, show, put on show, put on view, lay out, set out.
Screen Size	Partition, room, divider, dividing wall, separator.
Resolution dpi	Exhibit, show, put on show, put on view, dispose.

are applied according to this analysis result to alleviate FF. The efficiency of the proposed method is shown in the experimental result.

4. Experimental Result

One of the unpopular Samsung product (Samsung laptops) review is collected from the web for proposed work and this raw review is considered as input for the proposed work. In order to evaluate the proposed approach, 2000 sentences are crawled from web. Each sentence in is manually divided into three category, 1) Positive attitude about the usability PU, 2) Negative attitude about the usability, 3) NU and not about the usability NT. There are 260 PU sentences, 228 NU sentences and 1312 NT sentences.

In the data preprocessing phase list of stop words are removed and word stemming is performed to extract the word which represent the product feature. There are totally 50,000 words are there in the reviews. After preprocessing procedure 30212 words are removed in the sentences. The LDA Model and Lexicon algorithm creates the synonym dictionary. The dictionary form is shown in Table 3.

To evaluate the performance of the product usability the parameters such as Precision, Recall, F-Measure and its Accuracy are used. The metrics are measured by applying the Association Rule Mining with Fruit Fly Algorithm.

The precision and recall is calculated to find the correctly classified review sentence. Precision is calculated to identify how many review sentences are relevant and it is the fraction of total classified sentence that are relevant. The formula for precision calculation is:

$$\text{Precision} = \frac{n(\{\text{correctly classified review sentence}\} \cap \{\text{total classified review sentence}\})}{n(\text{total classified review sentence})} * 100\%$$

Recall is calculated to identify how many relevant review sentences are selected and it is the fraction of correctly classified review sentence from the total classified sentence. The formula for precision calculation is:

$$\text{Recall} = \frac{n(\{\text{correctly classified review sentence}\} \cap \{\text{total classified review sentence}\})}{n(\text{correctly classified review sentence})} * 100\%$$

F-Measure is calculated to find the test accuracy. It is mainly used in information retrieval field. It contains both the precision and recall value and F-measure is the weighted average of precision and recall. The F-measure is calculated by the following formula:

$$\text{fmeasure} = 2 * \frac{\text{precision} * \text{recal}}{\text{precision} + \text{recall}}$$

The following Table 4 and Figure 7 shows the results obtained after experimentation with the collected dataset.

The results of the above experiments made on product usability and Feature Fatigue analysis provides better accuracy and is shown in this section.

Table 3. Synonym dictionary

Metrics of Usability Classifier	Values
Precision	75.1569
Recall	87.6116
F-Measure	81.478
Accuracy	95.0058

Table 4. Performance metrics of usability classifier

Score	Description
9	Extremely attractive
7	Very attractive
5	Attractive
3	Somewhat attractive
1	Not attractive at all
8	Very attractive
6	Attractive
4	Somewhat attractive
2	Not attractive at all

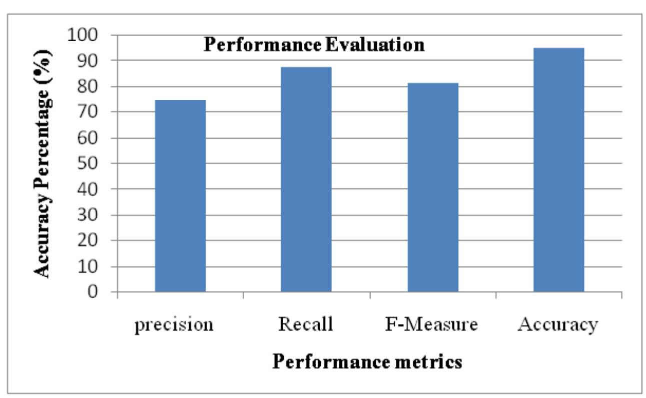

Figure 7. Performance evaluation report.

5. Conclusion

In this paper, the novel approach proposed with three phases evaluates the Product Usability and improves the Feature Fatigue. The customer review are collected through web crawler and proposed through NLP with LDA. Then Association Rule Mining with Fruit fly Algorithm is implemented to identify the review sentences. Finally Feature Fatigue degrees is measured by measured by evaluating the Product Usability and Capability to improve the Feature Fatigue. The results obtained shows better precision with 75%, Recall of 87%, F-Measure obtained 81.478% and the accuracy of the usability classifier is 95%. Further the proposed approach can be applied for various consumer products.

6. References

1. Li X, Hitt LM. Self-selection and information role of online product reviews. Information Systems Research. 2008 Dec; 19(4):456–74.
2. Chen Y, Chai Y, Liu Y, Xu Y. Analysis of review helpfulness based on consumer perspective. Tsinghua Science and Technology. 2015 Jun; 20(3):293–305.
3. Ghose A, Ipeirotis PG. Estimating the helpfulness and economic impact of product reviews: Mining text and reviewer characteristics. IEEE Transactions on Knowledge and Data Engineering. 2011 Oct; 23(10):1498–512.
4. Yoon BY, Kim SH. Effect of rest method on fatigue related factors and performance after submaximal exercise. Indian Journal of Science and Technology. 2015 Jan; 8(S1):384–90.
5. Wu M, Wang L, Li M, Long H. An approach of product usability evaluation based on Web mining in Feature Fatigue analysis. Computers and Industrial Engineering. 2014 Sep; 75:230–8.
6. Li M, Wang L, Wu M. A multi-objective genetic algorithm approach for solving feature addition problem in Feature Fatigue analysis. Journal of Intelligent Manufacturing. 2013 Dec; 24(6):1197–211.
7. Parikh SP, Esposito JM. Negative feedback for small capacitive touchscreen interfaces: A usability study for data entry tasks. IEEE Transactions on Haptics. 2012 Jan-Feb; 5(1):39–47.
8. Zhai Z, Liu B, Xu H, Jia P. Constrained LDA for grouping product features in opinion mining. Advances in Knowledge Discovery and Data Mining. Springer Berlin Heidelberg 2011 Jan; 6634:448–59.
9. Tassa T. Secure mining of association rules in horizontally distributed databases. IEEE Transactions on Knowledge and Data Engineering. 2014 Apr; 26(4):970–83.
10. Yoon YB, Kim SH. Effect of rest method on fatigue related factors and performance after submaximal exercise. Indian Journal of Science and Technology. 2015 Jan; 8(S1):384–90.
11. Ma B, Zhang D, Yan Z, Kim T. An LDA and Synonym Lexicon based approach to product feature extraction from online consumer product reviews. Journal of Electronic Commerce Research. 2013 Nov; 14(4):304–14.
12. Lin SM. Analysis of service satisfaction in web auction logistics service using a combination of Fruit fly Optimization Algorithm and general regression neural network. Neural Computing and Applications. 2013 Mar; 22(3-4):783–91.
13. Lizhen L, Wei S, Hanshi W, Chuchu L, Jingli L. A novel feature-based method for sentiment analysis of Chinese product reviews. Communications, China. 2014 Mar; 11(3):154–64.
14. Zhai Z, Liu B, Wang J, Xu H, Jia P. Product feature grouping for opinion mining. IEEE Intelligent Systems. 2012 Jul-Aug; 27(4):37–44.
15. Smitha P, Paul V, Shajy L, Sujathan K. Feature extraction from immunohistochemistry images to classify ER/PR Scores. Indian Journal of Science and Technology. 2015 Dec; 8(34):1–7.
16. Li M, Wang L, Wu M. A multi-objective genetic algorithm approach for solving feature addition problem in Feature Fatigue analysis. Journal of Intelligent Manufacturing. 2013 Dec; 24(6):1197–211.
17. Al-Shalabi R, Kanaan G, Jaam JM, Hasnah A, Hilat E. Stop-word removal algorithm for Arabic language. Proceedings of 1st International Conference on Information and Communication Technologies: From Theory to Applications, CTTA'04; 2004 Apr 19-23, p. 545–50.
18. Wu M, Wang L. Feature Fatigue analysis based on behavioral decision making. IEEE International Conference on Industrial Engineering and Engineering Management (IEEM); Singapore. 2011 Dec 6-9. p. 570–4.
19. Chinsha TC, Joseph S. A syntactic approach for aspect based opinion mining. IEEE International Conference on Semantic Computing (ICSC), 2015; Anaheim, CA. 2015 Feb 7-9. p. 24–31.
20. Mack Z, Sharples S. The importance of usability in product choice: A mobile phone case study. Ergonomics. 2009 Dec; 52(12):1514–28.
21. Kim IG. Effect analysis for LPGA Korean company sponsorship: Moderating effect of title sponsor and player endorsement. Indian Journal of Science and Technology. 2015 Mar; 8(S5):124–8.
22. Bullinaria JA, Levy JP. Extracting semantic representations from word co-occurrence statistics: Stop-lists, stemming and SVD. Behavior Research Methods. 2012 Sep; 44(3):890–907.

23. Wu M, Wang L, Long H, Li M. Feature Fatigue analysis in product development. Total Quality Management and Business Excellence. 2015 Feb; 26(1-2):218–32.
24. Wu M, Wang L, Li M, Long H. Alleviating Feature Fatigue in product development based on the bass model. Journal of Engineering, Design and Technology. 2015 Jul; 13(3):350–68.
25. Chai J, Wang L, Shi Q, Wu M. Alleviating Feature Fatigue of multi-generation products. Industrial Management and Data Systems. 2015 Sep; 115(8):1435–56.
26. Silva C, Ribeiro B. The importance of stop word removal on recall values in text categorization. Proceedings of the International Joint Conference on Neural Networks. IEEE; 2003 Jul 20-24. 3. p. 1661–6.
27. Xia H, Tao M, Wang Y. Sentiment text classification of customers reviews on the Web based on SVM. Sixth International Conference on Natural Computation (ICNC) IEEE; Yantai, Shandong. 2010 Aug 10-12. 7. p. 3633–7.
28. Santos CBDS, Alcaim A. Role of syllables and function-words in continuous Portuguese speech recognition. Electronics Letters. 2000 Jun; 36(12):1083–5.
29. Martínez-de-Pison FJ, Sanz A, Martínez-de-Pison E, Jimenez E, Conti D. Mining association rules from time series to explain failures in a hot-dip galvanizing steel line. Computers and Industrial Engineering. 2012 Aug; 63(1):22–36.
30. Agrawal R, Srikant R. Fast algorithms for mining association rules. Proc 20th Int Conf Very Large Data Bases, VLDB; 1994 Sep. p. 487–99.
31. Pan WT. A new Fruit fly Optimization Algorithm: Taking the financial distress model as an example. Knowledge-Based Systems. 2012 Feb; 26(1):69–74.
32. Han EH, Karypis G, Kumar V. Scalable parallel data mining for association rules. USA. ACM. 1997 Jun; 26(2):277–88.
33. Al-Maolegi M, Arkok B. An improved Apriori algorithm for association rules. International Journal on Natural Language Computing (IJNLC). 2014 Feb; 3(1):21–9.
34. Yabing J. Research of an improved Apriori algorithm in data mining association rules. International Journal of Computer and Communication Engineering. 2013 Jan; 2(1):25–7.
35. Wu M, Wang L. Feature Fatigue analysis based on behavioral decision making. IEEE International Conference on Industrial Engineering and Engineering Management (IEEM); Singapore. 2011 Dec 6-9.p. 570–74.