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Healthcare assessment for beauty centers using hybrid sentiment analysis

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ABSTRACT

Because of COVID-19, healthcare became the first interesting domain at the world. Here, comes the role of researchers to do what they can to guide people. Nowadays, the most wanted field is beauty industry. It achieved large market. And the estimation is toward the growing. Researchers can give advice to prevent unhealthy causes in this field. They can apply sentiment analysis methods to make decision whether a Beauty center is healthy or unhealthy. This work develops an improved method of sentiment analysis to classify the beauty centers in Iraq into healthy and unhealthy classes. Researchers used comments of beauty centers' Facebooks to perform the assessment. The methodologies encompass the two approaches lexicon-based and machine-learning-based. Three machine learning mechanisms had been applied; rough set theory, naïve bayes, and k-nearest neighbors. It will be shown that rough set theory is the best compared with the others two. Rough set theory achieved 95.2%, while Naïve Bayes achieved 87.5% and k-nearest neighbors achieved 78%.

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1. INTRODUCTION

The world after 2019 differs from its before. Health care became the first interesting domain at all countries, and for everybody. Many and many topics missing health care researches. The modern era directs people to be consumers of what is available to them. The motive is to achieve business deals for the benefit of kapitals in the world. People are drifting strongly toward the current, because of their desire to imitate, or in other words walk with the herd. Here comes the role of researchers to do what they can to guide people. The most wanted field is beauty industry. Its market size in 2020 was $483 billion. It is estimated to achieve $716 billion end 2025 [1], [2]. Researchers can give advice to prevent unhealthy causes in this field. They are applying text analysis approaches which are useful to make decision; healthy, or unhealthy.

Text analysis provides approaches to describe and interpret text's characteristics. As one of the common text analysis applications is document classification. Text may be structured-text; found in an organized form. Really, most examples of texts are unstructured-text such as chat-rooms. Analyzing structured-text is easier than analyzing unstructured-text. Today, sentiment mining from unstructured-text is the commonly used approach to classify text into negative or positive. Negative class gives advice that something is bad, so the decision will be leave it. While positive class gives advice that something is good, so the decision will be use it [3]-[5].

Sentiment analysis or in other words opinion mining; it is the extraction of negative or positive orientation that a writer feels toward some object. Extracting public sentiment became relevant for many and many fields from marketing to politics. That is because the extracted opinions are perfect in rating the product, the service, the person, or anything that the message is wrote about. Beauty centers could be evaluated by analyzing comments collected from social media sites. Comments are written by customers. Text orientation may be positive, negative or neutral [6]-[8].

Covid-19 increased the use of Facebook and other social media, forcing people to search about the suitable beauty center before deciding to get the service. Comments reflect tendencies of the customers of beauty centers. Iraqi beauty centers found at Facebook more than other social media. In beauty center Facebook, such as all others; comments provide implicit information. It may be subjective which based personality feelings. It makes decision according on events, so it is called opinionated. Or comments may be objective which based information, opinions, and evidences. So it is called factual [9]-[13].

It is good idea to apply sentiment analysis in healthcare domain. Smart healthcare makes it more efficient, more personalized, and more convenient. The new generation of information technologies is useful in transforming the traditional medical systems [14], [15]. The aim of current work is to make a decision whether a beauty center is healthy or unhealthy. The idea is to use customers' comments available across beauty centers Facebook to achieve the goal. Briefly, methodologies encompass; the construction of Arabic language/Iraqi dialect sentiment-lexicon, use it to apply sentiment analysis on collected comments, and then apply machine learning mechanisms to enhance results. In other words; hybrid sentiment analysis will be applied; lexicon-based phase, then the output will be input to machine-learning-based phase. Because comments in social media usually written in colloquial dialect. Therefore, perfect sentiment analysis lexicons must put that in response. Researchers collected comments from many beauty centers Facebook; they retrieved the comments that relevant to healthcare domain. And then they applied sentiment analysis to make decision whether a beauty center is healthy or unhealthy.

2. RELATED WORKS

The literature survey on web showed that; medical sentiment analysis researches are rare compared with other artificial intelligence applications in healthcare domain, and there is no Arabic sentiment analysis in healthcare domain [14]-[17]. Many attempts of lexicon-based and machine-learning-based sentiment analysis in Arabic language had been recorded in other domains. Following is exploring the Arabic lexicon-based, Arabic-machine-learning-based, and lastly the healthcare sentiment analysis attempts.

Abdulla *et al.* [18] focused the lexicon-based approach to sentiment analysis for Arabic language. They built a manually annotated dataset and the lexicon. Their experiments showed that more efforts are still needed to achieve accepted level of accuracy. They established a team with other researchers, who have produced many research papers in the field of sentiment analysis in Arabic [19]-[21]. Pamungkas and Putri [22] implemented lexicon-based sentiment analysis approach on Indonesian data opinion. They achieved accuracy of 0.68, which is considered as good result as a starting point for further research. Tag *et al.* [23] presented a lexicon-based approach for sentiment analysis of news articles.

Ismail *et al.* [24] trained four classifiers on a dataset consists of 4,712 tweets. They conducted a comparative analysis on the rendering of the classifiers (K-nearest neighbor, multinomial logistic regression, support vector machine, and naïve bayes). Hawalah [25] combined different Arabic linguistic features. He used the benchmark Arabic tweets datasets Arabic sentiment tweets dataset (ASTD) and ATA. He proved the evidence of using n-gram features in improving performance of machine learning classifiers. Mohamed *et al.* [26] built Arabic sentiment analysis classifiers models. They introduced a multi-criteria method to assess and rank their models. They assessed the performance of the top five machine learning classifiers methods (support vector machine, decision tree, naïve bayes, deep learning, and nearest neighbours). They used Saudi Arabic product reviews to apply their comparison. Following are some sentiment analysis paper researches in healthcare domain. Rasheed and Sadiq [27] suggested a model for assessing the departments' services. They assessed comments and reviews that are collected from social media pages of different Iraqies departments. They implemented the classification process by applying the algorithms; K-nearest neighbors, Naive Bayesian, and rough set theory.

Greaves *et al.* [28] say that understanding patient's experience of healthcare is a fundamental pillar of healthcare quality. Patients have begun to publish their healthcare experience on social networks, wikis, blogs, and on healthcare rating websites. NHS; which stands for "The information Strategy for the National Health Service (NHS)", in England assures that sentiment analysis of healthcare data could be a novel source of information. It will be valuable for patients when they try to choose a hospital.

Denecke and Deng [29] characterized the faces of sentiment in the medical domain. They retrieved their dataset from medical social media and clinical narratives. They performed a quantitative assessment that depending on word usage and sentiment distribution through the dataset. They concluded that word usage in medical social media differs from that in clinical narratives. They proved that the existing methods of sentiment analysis require adaptations because of the less subjective use of language in clinical narratives.

Yadav *et al.* [30] presented a benchmark setup that analyze the sentiment which respect to user's medical condition. They constrained themselves by some popular domains such as anxiety, asthma, depression, and allergy. They identified multiple forms of medical sentiments that inferred from users' medical condition, medication, and treatment.

Ramírez-Tinoco *et al.* [17] believed that healthcare domain is opened for researchers to performs sentiment analysis applications such as retrieve information about the diseases, patients' mood, adverse drug reactions, and epidemics. They proposed a sentiment analysis module to obtain sentiments and emotions on comments of texts related to the healthcare domain.

Abualigah *et al.* [31] saied that a huge volume of information concerned with healthcare found online. It could be collected from social media, personal blogs, and the websites. Ratings that are not obtained methodically may be constructed online. They assure the benefits of sentiment analysis in increasing healthcare quality. Medical information is perfect to achieve the best result.

3. SENTIMENT ANALYSIS

Sentiment analysis helps in; extracting, scoring, classifying, and visualize the opinions and the feelings that customers display when they review any service. Sentiment analysis research started at collecting documents that relevant with the desired domain. Next step is selection of the required data from the collected documents and then apply normalization on them. The origin idea from sentiment analysis is classification into two classes. Various types of classifiers have been successfully used. Bayes classification had been optimized to achieve sentiment analysis. Classification techniques of machine learning also applied successfully. All those classifiers are using all the words of known documents in the training stage as input. Then the output of training stage will be used to determine the class of unknown document in the testing stage. The must important and the old one, machine learning classification technique that is effective to achieve sentiment analysis; rough set theory [32], [33].

As an alternative model, there is lexicon-based, in which researcher focus only on certain words. Those words carry particularly strong cause to sentiment. These words called sentiment lexicons, which is decomposed into two lists, firstly is the list of positive terms, and secondly is the list of negative terms. The class of document is positive when it contains words belongs to positive list, and it is negative when it contains words belongs to negative list. Negative list as well as positive list usually includes two types of sentiment terms. A term may be single-word, or it may be double-word, as examples for positive sentiment; "likely" for single-word, and "very nice" for double-word; as examples for negative sentiment; "unlikely" for single-word, and "very bad" for double-word. While in Arabic language/Iraqi dialect sentiment-lexicon; the previous examples will be; محبيته, كلش حلو, حبيته, and كلش تافه, respectively. Sentiment analysis is either done on a document level or on a sentence level [34]-[37].

4. THE PROPOSED MODEL OF HEALTHCARE ASSESSMENT FOR BEAUTY CENTERS

The proposed model aims to assess beauty centers by applying hybrid sentiment analysis on Facebook comments. It receives comments written in Arabic/Iraqi dialect. It applies hybrid sentiment analysis, and then makes decision towards the beauty center or against it. The proposed model is decomposed into five main components as shown in Figure 1. It decomposed into; Arabic lexicon for positive and negative terms, text comments collection stage, the preprocessing stage, applying lexicon-based sentiment analysis stage, and machine learning-based sentiment analysis stage.

4.1. Arabic lexicon for positive and negative terms

This lexicon is the Arabic language/Iraqi dialect sentiment lexicon, which is provided by the previous work [13]. It provides words that have main role in the sentiment analysis process. It provides two types of terms; single-word terms and double-words terms. Each type has positive terms and negative terms. This lexicon includes; 520 single-words and 398 double-words. Single-word terms are divided into 215 positive and 305 negative. Double-words terms are divided into 218 positives and 180 negatives.

4.2. Text comments collection stage

This component is the first stage in the proposed model. Comments are collected from beauty centers Facebooks. Usually, for each new poster; customers write their comments that represent their; opinions, experiments; and emotions. So those comments are perfect in assessing healthcare of beauty centers. Firstly, comments are collected. Secondly, comments are filtered to remove documents that do not related with healthcare domain. Here, researchers discover that comments of beauty centers are mostly related to healthcare. The low percentage of comments that out of healthcare domain may be related to; the persons who work at centers, the place of centers, or the worktime.

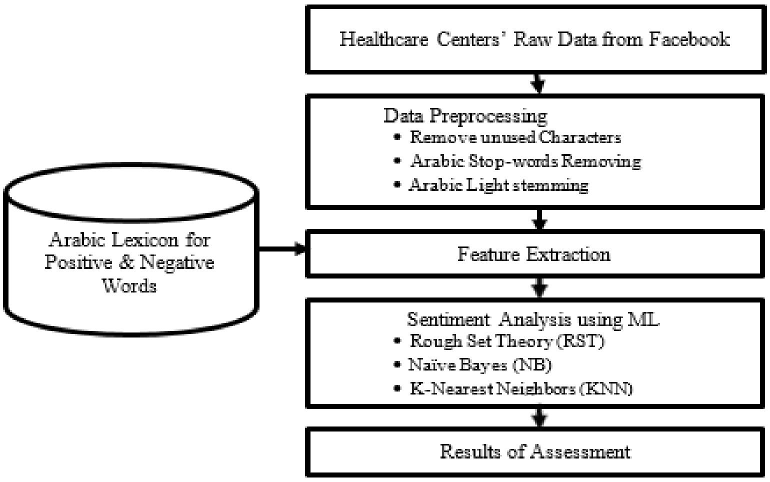

Figure 1. Healthcare assessment model for beauty centers: the main stages

4.3. The preprocessing stage

This is the second stage in the proposed model. It receives comments as character text. It transforms the text into a normal form, to be suitable for the next stage. This stage includes three processes; tokenization, stemming, and removing stop-words. Lite-stemming has been used.

4.4. Applying lexicon-based sentiment analysis stage

This stage receives normalized text. It used the provided lexicon to apply lexicon-based sentiment analysis on the received text. It marks received text as positive or negative according to the words found. Text that has words belongs to positive terms must be marked as positive. Text that has words belongs to negative terms must be marked as negative. While text that has both negative and positive terms must be marked as neutral. Also all texts with no positive or negative terms must be marked as neutral.

4.5. Sentiment analysis using ML stage

Lexicon-based sentiment analysis is not enough to achieve high accuracy results. By lexicon-based; it is difficult to solve ambiguity problems such as; text has words of two types negative and positive, text has no words belong to the lexicon. For all that; machine learning-based sentiment analysis is applied on the results of lexicon-based.

The proposed model uses word2vec (word to vector) technique has been used as a word vectorization method. Word2vec is very suitable in the most machine learning methods. The result of Arabic word2vec with Arabic lexicon words will be input to machine learning methods. This strategy is very suitable for sentiment analysis. Three machine learning algorithms are implemented here; rough set theory (RST), Naïve Bayes (NB) and K-nearest neighbors (KNN). The result of this component is the final result of the proposed model; the decision will be decided; positive, negative, or neutral.

5. EXPERIMENTAL RESULTS AND DISCUSSION

Now, the proposed model is experimented with the collected text comment from Facebook. The dataset is collected from 48 Iraqi beauty centers Facebook. Details of the collected dataset are shown in Table 1. Researchers took in consideration 48 beauty center's pages in the Facebook. They used 7 posts from each beauty center Facebook. After filtering comments unrelated to healthcare domain, they selected 40 documents from each post. The total sentences from all documents were 30,560.

Table 1. Stats of dataset

Pages	Posts	Comments	Sentences
48	336	13,400	30,560

Firstly, the lexicon-based sentiment analysis stage was applied for 13,400 comments. After that, the three machine learning classification methods (RST, NB and KNN) had been implemented. Figure 2 shows the accuracy ratio of the three classification methods after applying on the current dataset to achieve sentiment analysis. The best one is RST. The confusion matrix of the classification algorithm RST is shown in Table 2. For more details; the Tables 3-5 have been shown the detailed confusion matrices; positive sentiment, negative sentiment and neutral sentiment of the 13,400 comments respectively.

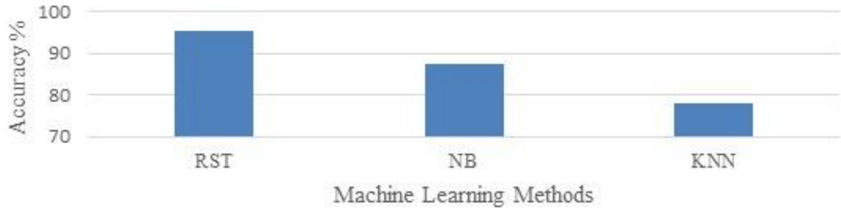

Figure 2. Sentiment analysis accuracy

Table 2. RST confusion matrix for 13,400 comments' sentiment classification

		Predicated Class			
		Positive	Negative	Neutral	Total
Actual Class	Positive	7,596	121	263	7,980
	Negative	112	4,520	228	4,860
	Neutral	18	32	510	560
					13,400

Table 3. Positive sentiment confusion matrix

		Predicated Class		
		Positive	Non-Positive	Total
Actual Class	Positive	7,596	384	7,980
	Non-Positive	130	5,290	5,420
				13,400

Table 4. Negative sentiment confusion matrix

		Predicated Class		
		Negative	Non-Negative	Total
Actual Class	Negative	4,520	340	4,860
	Non-Negative	153	8,387	8,540
				13,400

Table 5. Neutral sentiment confusion matrix

		Predicated Class		
		Neutral	Non-Neutral	Total
Actual Class	Neutral	510	50	560
	Non-Neutral	491	12,349	12,840
				13,400

The accuracy of binary classifier is calculated by (1) [38]:

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \quad (1)$$

Now, by applying (1) on data from Tables 2-4, it could be shown that the accuracy of; positive comments achieved 95.2%, negative comments achieved 93%, and neutral comments achieved 91%. Furthermore, the average of per-class effectiveness value of the classifier, which is called as the average accuracy is calculated using (2) [38]. The resulted average accuracy reached to 96.14%.

$$Average\ Accuracy = \frac{\sum_{i=1}^{l}\frac{TP_i+TN_i}{TP_i+FN_i+FP_i+TN_i}}{l} \quad (2)$$

Where, l is the total number of classes.

The per-class classification error average, the average error rate, is calculated by (3) [38]. It reached to 3.8%.

$$Average\ Error\ Rate = \frac{\sum_{i=1}^{l}\frac{FP_i+FN_i}{TP_i+FN_i+FP_i+TN_i}}{l} \quad (3)$$

The precision computation is calculated by applying (4) [38]. It calculates the average per-class agreement between the human judgment with the classification model which yielded about 93.06%.

$$Precision = \frac{\sum_{i=1}^{l} \frac{TP_i}{TP_i + FP_i}}{l} \tag{4}$$

The recall computation is calculated by applying (5) [38]. It is average of the agreement between the human judgment and the classification model, per-class. It reached to 82.1%.

$$Recall = \frac{\sum_{i=1}^{l} \frac{TP_i}{TP_i + FN_i}}{l} \tag{5}$$

The assessment of healthcare for Iraqi beauty centers by applying hybrid sentiment analysis of customer's comments in the centers Facebook pages. Table 6 shows the results.

Table 6. The results of healthcare centers assessment

Positive Sentiment Range	Negative Sentiment Range	Assessment
≥ 80%	None	Very Good
≥ 70% & < 80%	None	Good
≥ 60% & < 70%	*≥ 10% & < 20%*	Medium
≥ 50% & < 60%	*≥ 20% & < 30%*	Acceptance
Otherwise	Otherwise	Bad

The applying of above rules on 48 Iraqi beauty centers discovers that; 21% have very good healthcare assessment, 24% have good healthcare assessment, 28% have medium healthcare assessment, 9% have acceptance healthcare assessment and 18% have bad healthcare assessment. Figure 3 illustrates these results.

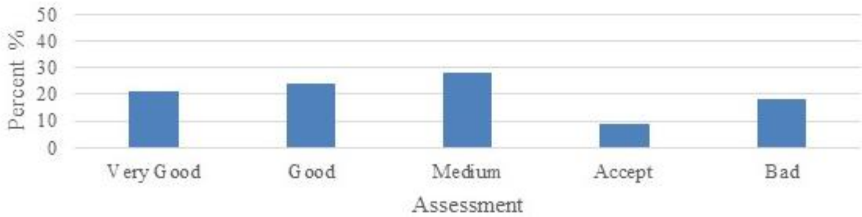

Figure 3. Iraqi healthcare centers assessment

Through the experiments that were conducted and testing the progress of the classification process, we found that rough set theory was the best method because it works to find the best relationships among the text words through the lower and upper boundarires. The lower and upper boundarires in the rough set theory can exploration the best features in the text, especially with the power of lexicon.

6. CONCLUSION

Iraqi customers express their opinions using Iraqi dialect. Sentiment analysis models that applied on Iraqi dialect have more advantages than others because of dealing with real data. In Iraqi dialect, positive and negative sentiment could be achieved from terms decomposed into single or double words. The proposal is provided with Iraqi dialect lexicon that is covered all expected terms of single and double words. Because of lexicon-based sentiment analysis disadvantages, it is not enough to achieve believed results. The proposal made useful of provided lexicon to classify collected documents, then applied machine learning-based sentiment analyses to enhance results. It applied three machine learning classification methods; RST, NB and KNN. RST achieved the best results compared with others two, because of its great benefits for categorized data. Although the great benefits, RST has no ability to reach accuracy of 100%. Because such analysis needs semantic features to achieve results matched to the reality without any error rate.

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