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Facebook Comments-Based Assessment Model for Food Product Companies Using Four Machine Learning Methods with Arabic/Iraqi Lexicon

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Abstract

People's need for food is increasing day after day due to the large population increase that has occurred in human society, which has led to a significant increase in the activity of food product manufacturing companies in the world. Hence the necessary need to evaluate the performance of food production companies. We found that the best way to evaluate the performance of these companies is through social media comments, because it is the newest and most common method among people. In this paper, 4 machine learning techniques were relied upon to evaluate participants' comments in evaluating food production companies after using a lexicon of Arabic language terms in general and the Iraqi dialect in particular. These terms relate to positive and negative words and expressions. Then training through machine learning algorithms. Random Forest (RF), Naive Bayes (NB), Rough Set Theory (RST), and Support Vector Machine (SVM) algorithms were tested. Experiments have shown that RST is superior to the other three. RST achieved (96.13%), SVM achieved (95.75%), although RF achieved (94.1%) and NB achieved (87.1%).

Keywords: Assessment Model, Facebook Comments, Food Product, Iraqi Dialect Machine Learning.

Introduction

Social media has become increasingly popular over the past few years, and people use it to express both thoughts and experiences. A practice that is growing more and more popular is posting or sharing visual, audio, and textual content on social media platforms. Food production rose to the top of everyone's interesting topics in all nations. Many subjects lack study on food goods. People are encouraged to be consumers in the modern era by their surroundings. The goal is to close business deals that will benefit global capital. Due to their drive to conform, or more accurately, to follow the crowd, people are strongly flowing in the direction of the tide. Researchers now have a responsibility to help people in whatever way they can. Evaluating social media for food goods in Iraq is the most sought-after field. In this area, researchers might offer guidance on how to avoid hazardous causes. They are using text analysis techniques that help them decide whether a choice is unhealthy or healthy[1].

Methods for describing and interpreting the features of text are provided by text analysis. Document classification is a popular text analysis application. Structured text is text that has been organized. Actually, chat rooms and other forms of unstructured text make up the majority of examples. Structured text is simpler to analyze than unstructured text.

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Currently, the method most frequently utilized for classifying text as negative or positive is sentiment mining from unstructured text.

Negative class suggests leaving something away since it is bad. Positive class informs us that something is good[1- 3], therefore it is used in this paper. Sentiment analysis, also referred to as the opinion mining, can be defined as the act of figuring out whether a writer has positive or negative attitude concerning a certain issue. Getting the public's opinion is now crucial in a variety of fields, like politics and marketing. This is because opinions which were extracted from the message can be used to rate items, services, persons, and so on.

Social media for food goods can be assessed by looking at the comments gathered from social media sites. Customers post comments on websites. Negative, positive, or neutral text orientations are possible[4-6]. Because of Covid-19, more people are using Facebook and other social media, which forces them to research the best food items social media before selecting whether or not to purchase the service. Customer trends are reflected in comments on websites selling food products. Social media for food goods in Iraq, more frequently found on Facebook than other social platforms. Like all other Facebook pages, Food products' comments contain implicit information. It might be based on a person's subjective feelings. It is referred to as opinionated since it makes decisions based on occurrences. Comments could be factual and supported by data, arguments, and views. Consequently, it is said to as factual[7-9]. Applying sentiment analysis to the social media space for food goods is a good concept. Social media for good food products makes it more effective, more individualized, and more practical. The conventional systems can be transformed with the help of the next generation of information technologies[10, 11].

The objective of the ongoing research is to determine if a food product is bad or good. To accomplish the purpose, it is proposed to use customer reviews that are available on Facebook for food-related social media. In a nutshell, procedures include creating an Arabic language/Iraqi dialect sentiment-lexicon, used for doing sentiment analysis on the comments that have been gathered, and then implementing ML techniques to improve outcomes. Lexicon-based phase of hybrid sentiment analysis will be used, and the outcome will be input to ML phase, since social media comments are frequently written in dialect. Therefore, that must be a response in ideal sentiment analysis lexicons[12, 13]. Academics gathered feedback from several users of the social media platform Facebook for the food industry, and they selected the remarks that were pertinent to the industry. They used sentiment analysis to determine the quality of food products.

The contribution of this paper is the classification of food products in Iraq into classes using sentiment analysis. For the assessment, this research analyzed Facebook comments on food products. It used sentiment analysis techniques for determining whether or not a food product is good. The rest sections of this paper proposed used the specified lexicon to categorize the texts that were collected, and after that sentiment analysis depending on ML were used to improve the results. RST, SVM, RF and NB were four machine learning classification techniques that were used. RST, which has excellent advantages for categorized data, produced the best results when put to comparison with the other three.

Related Works

The problem of evaluating food production, we did not find research that addresses this topic from a scientific perspective.

The online literature review revealed that, in contrast to other AI applications in the food industry, food product sentiment analysis studies are very uncommon.

Garouani and Kharroubi [14], this research study concentrated on the Arabic language's lexicon-based technique to sentiment analysis. In addition, they created lexicon and a dataset that was manually annotated. Their research revealed that additional work is still required to reach a level of accuracy that is considered acceptable.

Aloqaily et al. [15], this study discusses both approaches for SA in Arabic. Due to the dearth of publicly accessible Arabic datasets and lexicons regarding SA, such study begins through creating a manually annotated dataset before walking readers through each step in great detail. Throughout the various steps of this process, experiments are carried out to track the system's accuracy gains and compare them to corpus-based approaches.

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Duwairi et al. [16], the authors employed sentiment lexicon. The lexicon has been produced by the translation of SentiStrength English sentiment lexicon to Arabic and after that supplementing it using Arabic thesauri. A set that consists of 4,400 Arabic tweets has been gathered and manually annotated by the writers. With the use of the suggested framework, such tweets were divided into negative or positive categories based on their sentiment. The findings show that lexicons are useful for sentiment analysis.

Mustafa HH [17], this study offered a brand-new hybrid lexicon technique with regard to Arabic sentiment analysis which combine unsupervised and supervised methods into a single framework. Using the Lookup table stemming method, data polarity is extracted during the unsupervised phase. With regard to the supervised phase, in[17] create and train a classifier to further classify the unclassified data using the data regarding true classified polarity from unsupervised phase. With the use of MIKA corpus, the authors evaluated and tested the suggested method. Furthermore, outcomes demonstrate that the proposed technique produces superior outcomes.

Machová et al.[18], the sentiment analysis approach for opinions from data was lexicon-based in the presented study. It solves two problems. The first problem is related to lexicon labeling. The second problem is classification of texts which do not contain words from the lexicon proposed methods, based on a machine learning , They obtained an classify more than 99%, which is seen to be a good result as starting point for more researches.

Taj et al.[19], in the presented paper, lexicon-based technique for news article sentiment analysis is provided. The trials had been performed on the BBC news data-set from 2004 - 2005, proving reliability and suitability of the selected method. Was showed the result comments sports and business had more positive, whereas tech and entertainment had a majority of negative articles.

Ismail et al.[20] This paper extracting and analyzing Twitter data in Sudanese dialect to discover opinionated patterns the quality of telecommunication operating in Sudan. This research used a dataset of 4,712 tweets to train four classifiers. The performance of the classifiers (KNN, SVM, multinomial logistic regression, and NB) was compared. The results revealed that the best accuracy was achieved by KNN it equals to 92.0.

Hawalah[21], various Arabic linguistic features were combined in this work, the author made use of the benchmark Arabic sentiment tweets dataset (ASTD) as well as ATA. The author demonstrated the effectiveness regarding n-gram features in enhancing the performance of ML classifier.

Abo MEM et al.[22] The work created models for Arabic sentiment analysis classifiers. Furthermore, the researchers developed a multi-criteria evaluation as well as ranking system for the models. Also, top five ML classifier approaches (SVM, DT, NB, DL, and nearest neighbors) were evaluated for performance. For their comparison, they utilized Saudi Arabic product reviews.

Rasheed and Sadiq[23], a model for assessing the departments' services was proposed by this work. They evaluated comments and reviews gathered from various departments of the Iraqi government's social media pages. They used KNN, naive Bayesian, and basic set theory techniques to implement the classification procedure.

Greaves et al.[24], the authors utilized Weka DM software for employing ML techniques on a total of 6,412 on-line comments pertaining to hospitals on English National Health Service website in the year 2010. Spearman rank correlation was employed by the authors to examine the sentiment analysis outcomes against the outcomes of national inpatient survey conducted on paper at hospital level, encompassing all 161 acute adult hospital trusts in England. The study found that there was a significant level of agreement between the quantitative care ratings and these generated from the free-text comments utilizing sentiment analysis, with kappa scores ranging from .40 to .74 and $P<.001$ for all. Specifically, there was agreement of 81% for cleanliness, 84% for being treated with dignity, and 89% for general hospital recommendation. The study authors discovered that there existed weak to moderate correlations (Spearman rho 0.37 to 0.51; $P<.001$ for all) between the predictions generated by ML model and the responses obtained from the extensive patient survey, for the three categories that were being evaluated.

Abualigah et al[25], this research described the various forms regarding sentiment in medical field. The authors obtained the dataset from clinical narratives and medical social media. Furthermore, the authors carried out quantitative analysis based on the dataset's word usage as well as sentiment distribution. They came to the conclusion that the words used in clinical narratives and medical social

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media is different. Also, the authors demonstrated that the existing sentiment analysis techniques need to be modified due to less subjective language used in the clinical narratives.

Yadav et al.[26], in this work, a benchmark configuration was offered that assesses user sentiment with regard to their medical condition. They were limited by some well-known fields, like asthma, anxiety, depression, and allergies. They discovered a variety of medical feelings that were implied by the users' conditions, medications, and treatments.

Abualigah et al.[27], online, there is a vast amount of information about healthcare. It might be gathered via websites, social media, and personal blogs. Online ratings that are not created deliberately are possible. They guarantee that sentiment analysis will improve the standard of healthcare. Information in the medical field is ideal for getting the greatest outcome.

Sentiment Analyses

Sentiment analysis assists in the scoring, extraction, classification, also visualizing feelings as well as opinions which clients express in the case when reviewing any service. The first step in sentiment analysis study was gathering relevant documents for the target domain. The next step is to choose necessary data from documents that were collected and after that apply normalization to it. The notion for classification into two classes comes from sentiment analysis. Different classifiers were employed with success. To perform sentiment analysis, Bayes classification had been optimized. ML classification approaches have also been efficiently used. All of the classifiers use the words from well-known documents as input during the training phase. In the testing step, the class of unknown document will after that be determined using the training stage's results. The most significant and traditional ML classification method, rough set theory, is effective in achieving sentiment analysis[28,29]. Lexicon-based research is an alternate strategy in which researchers concentrate solely on specific words. The sentiment behind those statements is especially strong. Those concepts are referred to as sentiment lexicons; they are divided into 2 lists: one for negative terms and the other for positive terms. When a document contains words from a positive list, it belongs to positive list; in a case when it includes words from a negative list, then it belongs to the negative list. Two categories of sentiment terms are typically included in negative as well as positive lists. A term might be a double word, or a single word with the word "likely" with regard to single word, while "very nice" regarding double word as positive sentiment examples; the terms "unlikely" and "very bad" are examples of negative sentiment, with the former being a single word and the latter being a for double word. In terms of Arabic language/Iraqi dialect sentiment-lexicon; previous examples will be, طيب, كلش لذيذ, مطيب, كلش تعبان. Either a sentence level or document level analysis of sentiment is performed[30–33]. Fig. 1 depicts the key phases of sentiment analysis.

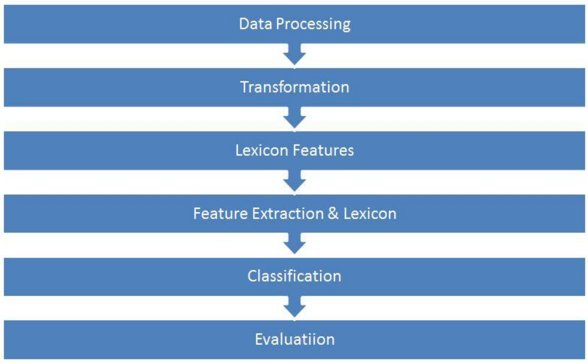

Figure 1. Sentiment analysis main stages

The Proposed Model

The suggested approach utilizes hybrid sentiment analysis on Facebook comments to evaluate social media for food products. It receives comments in the dialect of Arabic spoken in Iraq. It uses hybrid sentiment analysis before deciding whether to be pro- or anti-food product social media. As illustrated in Fig. 2, the suggested model is broken down into five key parts. The breakdown consists of several stages, namely the collection of text comments, the application of lexicon-based sentiment analysis, pre-processing stage, as well as ML-based sentiment analysis stage. The lexicon that has been utilized in this study pertains to both negative as well as positive terms in Arabic lexicon.

Arabic/Iraqi Lexicon for Negative and Positive Terms

This lexicon, which has been based on earlier work[3], is Arabic language/Iraqi dialect sentiment lexicon. Primary words that have been used in the sentiment analysis procedure are provided. It offers terms with a single word and terms with two words. Negative and positive terms exist for each type. There are 520 single-words and 398 double-words in this lexicon. There are 305 negative and 215 positive single-word terms. Terms with two words

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are split into 180 negative and 218 positive categories. An Example words are available Iraqi Lexicon for negative and positive terms as seen in Table 1.

Table 1. An Examples of Arabic/Iraqi Lexicon for negative and positive terms

Positive words	Negative words
تسلم ايدك	سيء الحظ
good job	Bad luck
الأكل طيب	الأكل مو نظيف
The food is good	The food is not clean
عفيه	مخادع
Excuse me	Deceptive
تازة	متعفن
new	moldy

Text comments collection

The suggested model's initial stage is represented by this component. Facebook social media for food goods is used to gather comments. Customers typically leave comments for each new poster that reflect their experiments, emotions, and opinions. Therefore, those comments are ideal for analyzing websites that sell food. First, comments are gathered. Second, documents that have no relation to the food items are removed from comments. Researchers find that the majority of social media comments about food products are related to food products. The low number of comments from beyond food products could be attributed to the staff members at centers, the location of centers, or the hours that they are open.

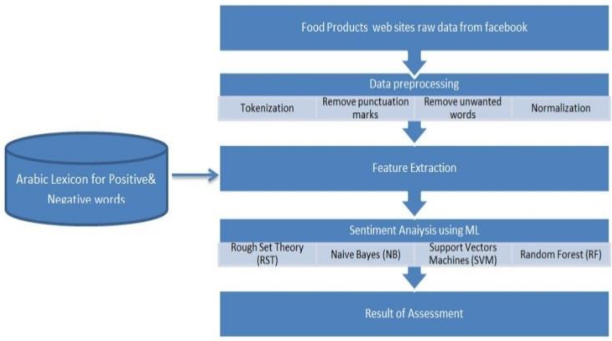

Figure 2. Food products assessment model for Food products social media Facebook: the main stages

The Preprocessing

Online texts often contain noise data such as HTML tags, punctuation, links, scripts, and other forms of noise. The presence of noise data in social media texts assessing food products can pose a significant obstacle to the identification of influential words. Therefore, it is imperative to adopt a preprocessing methodology to eliminate such data as their retention could render classification process more complicated, given that every data point may be assessed as singular dimension. Tokenization, punctuation removal, removing unnecessary words, normalization, and removing stop words are preprocessing steps.

Tokenization

The sequence of texts was divided into a sequence of words in this step. The tokenization technique of dividing the text into words has been shown in Algorithm1.

```
Algorithm1: Tokenization
 Inputs: Texts T
 Tok ={ }, list of tokens
 For each T in dataset do
       Tok.append (Ti), split texts into tokens
Outputs: Tok, list of tokens (words)
```

Removing Punctuation Marks

Punctuation marks make the line of coherence connecting sentences, paragraphs, and phrases easier to understand and read. The Arabic language uses a variety of punctuation marks, including apostrophes, commas, quotes, and question marks. It is required to remove any punctuation marks once the texts have been divided into words by the tokenization procedure, which involves using white spaces to separate the texts into words.

Removing Unwanted Words

This process gets rid of a lot of extraneous words like English or Arabic numbers, non-Arabic words or characters, and others which aren't in punctuation. Many regular expressions are available to accomplish this, as seen in Table 2.

Table2. List of Regular Expression

Regular Expression	Results
[a-zA-Z]+	Remove English characters
[0-9]+	Remove Arabic digits
[0-9]+	Remove English digits
#$%|@^~(&*)+	Remove others

Stop Words Removal

Upon comparison with the list of Arabic stop words, it is possible to eliminate the Arabic stop words from

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a given article. The present study employed two stop words lists for the purpose of analysis. The first list was created with the use of NLTK library in Python, and the second list contains words that are irrelevant to the sentence. The steps for removing stop words are shown in Algorithm 2.

Algorithm 3: Stop Words Removal
Input: (Tokens) Tok, list of normilization words
Tok = {Tok1, Tok2, …. Tokn} where n number of tokens in the text
SW = {SW1, SW2, …., SWm}, list of the stop words
S = { }, new words list with no stop words
For each Toki in Tok Do
    For each SWj in SW Do
        If Toki not in SWj Then
            Append Toki to SWj
Outputs: S, new list of the words that don’t contain any stop words

Normalization

The process of Arabic text normalization involves transformation of textual material to single canonical structure, i.e., pre-processing text for normalization purposes facilitates the separation of concerns by ensuring that the input is uniform before any operations are performed on it. In this study, the V1 dataset was subjected to normalization and conversion into a uniform format. This was deemed necessary due to the inherent variability in the shapes of Arabic words, which can result in a high-dimensional feature space and reduced accuracy. Normalization comprises of three distinct steps, namely the elimination of tatweel, the elimination of diacritics, and the normalization of letters. Initially, the diacritical marks are removed from the Arabic word, and subsequently, it is transformed into a distinct word utilizing the alphabet. Fig. 3 displays the diacritical marks that are eligible for removal. In the case when the approach is not utilized, there will be a lot of words, after that increasing the size of search area and the amount of time needed. For example, ("تعبيراً") become ("تعبيرا"), in the case when diacritic ("ً") has been removed from the word, there will be one word left.

Figure 3. Arabic Diacritics

Tatweel in Arabic language indicates any character which specifies elongation (———) and is referred to as ("تطويل") as well. It increases length of the line of text through the expansion of the spaces between words or separate letters. For instance, "كاروـــــــــنا", "كاروـــــنا" and "كاروـــنا" it is the same word as "كارونا". The crucial last step in the process of normalization involves creating a distinctive letter for certain letters. Arabic characters can be written in various ways, as shown in Table 3.

Table3. Latter Normalization of Arabic Language

Original	Become	Example	
إأآا	ا	أعتماد Approval	اعتماد Approval
ى	ي	سخى Generous	سخي Generous
ؤ	ء	اداؤه performance	اداءه Performance
ة	ه	بيتزة Pizza	بيتزه Pizza
ئ	ء	بائع vendor	باءع vendor

In this study, normalization has been shown in algorithm 3.

Algorithm 3: Normalization
Input: Texts *T*
Tok = {Tok_1, Tok_2, Tok_n} from Algorithm 1
For each Tok_i in Tok
- Remove diacritics from every Tok_i as Fig. 3
- Eliminate any Tatweel
- Normalization of letters like in Table 2

EndFor
Outputs: *Tok*, list of the normalized words

Root Stemming

The suggested stemmer includes many steps as can be seen in algorithm 4.

Algorithm 4: ISRI Stemmer
Inputs: words
Remove length 3 and 2 suffixes
Remove length 3 and 2 prefixes
Remove connecting و in the case where it’s in the start of a word
If length(word)<=7 && length(word) >=4
    If length(word) = 4
    Extract matches with list of the patterns like (فاعل,فعول,فعله, …)
    If length(word) = 5
    Extract matches with list of the patterns like (تفاعل,تفعيل, …)
    If length(word) = 6 then
    Extract matches with list of the patterns like (استفعل,افتعال, …)
If length(word) = 7 then
Remove 1 character suffix or prefix in the case where it matches the pattern list of (ك,ا,ن,ت,ل)

Light Stemming

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Arabic is a very distinct language with regard to its stemming since it has large vocabulary, a large collection of synonyms, and a complex grammar. Due to this, there must be specific guidelines on how to handle the word additions (prefixes, suffixes). One of the most crucial steps in creating dataset V3 is this one. It eliminates linguistic additions like suffixes and prefixes. As a result of being restored to their original forms and being expressed in a single form, all words are said to have one origin. Therefore, this stemmer's implementation results in a decrease in both space and time, increasing its efficiency in handling all rules. Through changing ISRI stemmer, that is a set of criteria determining the way for applying stemming on a particular word, a method for Arabic light stemmer was presented. Rules of the removal of waw ("و"), suffixes, and prefixes in the Arabic light stemmer. Table 4 illustrates the rules of waw, suffixes, and prefixes that were constructed. These rules, which were gathered from ISRI, are just written in the manner described above; they differ significantly from the original algorithms, which involved numerous phases.

Table 4. WaW, Suffix, and Prefix

Methods	Length of word	Letter Removed from word	Letters
WaW	W >= 4	1	و
Prefix	p>=6	3	كال, بال , ولل, وال
	p>=5	2	لل, ال
Suffix	s>=6	3	تمل, همل , تان, كمل, تين
	s>=5	2	ون, ين, تن, كم, ات, ان, هن, ها, تم, كن, ني, نا, يا, وا, ما,هم

The algorithm5 shows light stemming steps.

```
Algorithm5: Light Stemming
Inputs: S, list of words
S = {S1, S2, …., Si} list of words from the step of pre-processing
LS = { }, Empty light stem words' list
For each Si in S Do
        Removing ("و")
        Removing the prefix belong to Table 3
        Removing the suffix belong to Table 3
    Append Si to LS
Outputs: dataset V3, LS, list of the light stemming words
```

Arabic/Iraqi Lexicon-based sentiment analyses stage

Lexicon-based method is unsupervised approach that mainly makes use of sentiment lexicons. Basic Lexicon method is used to count the number of the negative and positive terms in the documents and phrases[34]. Texts are regarded to have a positive feeling in the case when there are more positive terms in comparison with negative ones[35]. LABR lexicon is the particular manual lexicon for LABR dataset[36]. In total, it has 874 qualities. Sentiment score corresponds to each one of the words in LABR's sentiment lexicon. With regard to LABR dataset's special sentiment lexicon, each one of the terms from a dataset of Facebook comments correlates to an opinion characteristic. The sentiment findings are determined as negative or positive by adding up sentiment scores for all terms in Facebook comments. The assessment was deemed positive if there were more positive terms than negative ones; or else, it was deemed negative. Depending on the proportion of words in the comment, it is classified as either negative (-1) or positive (+1) in two categories.

Sentiment Analyses using Machine Learning

Lexicon-based sentiment analyses are unable to generate highly accurate results. It could be difficult to address concerns of ambiguity in texts that have both negative and positive texts or words that don't contain any words from lexicon when employing a lexicon-based method. The results are subjected to lexicon-based sentiment analysis to account for everything. The suggested model utilizes word2vec (i.e. word to vector) method as word vectorization technique. The majority of ML techniques are very compatible with word2vec. Arabic word2vec output containing Arabic lexicon words will be fed into ML approaches. This approach is ideal for sentiment analysis. Here, the NB, rough set theory (RST), SVM, and RF machine learning methods are all conducted. This component's output determines the suggested model's eventual outcome and whether it will be negative, positive, or neutral.

Rough Set Theory (RST)

RST[37] is used for handling uncertainty and incompleteness. A lower and upper approximation of a set, also related models of sets as well as approximation space, are all taken into account by RS theory. Attribute reduction, or the deletion of least informative attributes, are crucial applications of RS theory. In the case when equivalence relations

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are generated through comparing sets of characteristics, attribute reduction could be accomplished. When attributes are removed using the dependence degree as a measurement, the smaller attribute set nevertheless delivers the same degree of dependency as original set. In order to make the analysis carried out in this work easier, RS theory principles will be present in this part. The RS theory and its principles are fully discussed. An information system is utilized for representing the knowledge in the rough sets, that has been given as 4 tuple IS D<U; A; V; f >, where U denotes closed universe, a finite set pertaining to the N objects $\{x_1, x_2, \ldots x_n\}$, and A denotes a finite set of the attributes $\{a_1, a_2 \ldots a_n\}$ which might be further divided into 2 disjoint subsets i.e., C and D, A D C [D, where C defines the condition attributes and D signifies a set of decision attributes. Set V D Va, where Va refers to a domain of the attribute a, while f V U × A | V relates to the total decision function, referred to as the information function, wherein f (x; a) to Va for each a 2 A; X 2 U. In RS theory, the upper and lower approximations are regarded as two basic operations, related to any concept X ⊆ U, while attribute set R ⊆ A, and X can also be approximated via the upper and lower approximations. The lower approximation pertaining to X can be defined as a set of objects of U that are certainly in X, represented as:

$$\overline{R}(X) = \{x \epsilon U : [x] R \subseteq X\} \qquad 1$$

The set of U objects which might possibly be in X is known as the upper approximation for X and is denoted as follows:

$$\underline{R}(X) = \{x \epsilon U : [x] R \cap X \neq \emptyset\} \qquad 2$$

Naïve Bayes (NB)
Because of its simplicity and efficiency, the NB algorithm is a well-liked ML method for sentiment analysis[38, 39]. The likelihood that a document will belong to the class $C_k \in$ positive; negative when given a set of N reviews r_j, in which each one of the reviews is indicated as a series of m terms $r_j = t_1, t_2, \ldots, t_n$ is given as follows:

$$p(C_k|r_j) = p(C_k)\prod_{i=1}^{m} p(t_i|C_k) \qquad 3$$

Where $p(t_i / c_k)$ represents term t probability which occur in a review of class C_k and $p(c_k)$ is prior probability of a review which occur in a class C_k and $p(c_k / r_j)$ have been estimated from the training data.

Support Vector Machines (SVM)
It has been demonstrated that SVMs are quite good at classifying sentiment. SVMs typically perform better than other classifiers. In addition, SVMs look for a decision hyper-plane that has been represented through support vector that clearly divides training vectors for negative and positive data. Hyper-planes are used by SVMs to divide classes[40].

Random Forest (RF)
A supervised learning model, or RF, is a more advanced variation of DT. With regard to RF, a substantial number of DTs independently anticipate the outcome regarding each one of the classes, with the class receiving the most votes determining the final prediction. RF has a lower error rate compared to other models since there is less correlation between trees[41]. The RF model has been trained using a range of parameters, in other words, different numbers of the estimators have been utilized in grid search, to discover the optimal model which could accurately predict the result. Based on the classification or regression task, different methods could be used to determine a split in DT. This work used Gini index as cost function for estimating a split in the data-set for the classification task. Gini index has been calculated by the subtraction of the summation of squared probability for every class from one. The following mathematical formula is used for calculating G_{ini} index (G_{ind})[42].

$$G_{ind} = 1 - \sum_{i=1}^{c} (P\,i)^2 \qquad 4$$

Results and Discussion

The suggested model is currently being tested using the Facebook text comments that have been gathered. The dataset was gathered from (12) Facebook pages dedicated to Iraqi food goods. Table 5 displays specifics of the dataset that was gathered. Facebook social media profiles for food products were taken into consideration by the researchers. They made advantage of (15) posts from each Facebook page for food products. They chose between 80 and 85 comments from each post after removing those not relevant to the topic of food products. There were 15000 sentences in all of the comments.

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Table 5. Stats of the data-set

Pages	12
Posts (from each page)	15
Comments (from each posts)	80 - 85

The initial stage of sentiment analysis using lexicons was applied to 15000 comments. The three ML classification approaches (NB, RST, RF, and SVM) were subsequently put into practice. Following application on current dataset for achieving sentiment analysis, Table 6 displays the accuracy ratios of the four classification approaches. RST is the most accurate, with a value of 96.13%. Table 3 displays the RST classification algorithm's confusion matrix. For further information, see Tables 7-9, which contain extensive confusion matrices for the (15000) comments' negative, positive, and neutral sentiments.

Table 6.Accuracy Ratio for 4 Machine Learning methods

Classification Method	Accuracy (%)
RST	96.13
SVM	95.75
RF	94.6
NB	87.1

Through Table 6, it was shown that the best method is RST. Therefore, we confirm the results of this method by analysis and separate the results through the Confusion matrix.

Table 7. Confusion matrix for (15000) comments' sentiment with the use of RST

		Predicated Class			
		Positive	Negative	Neutral	Total
Actual Class	Positive	8900	155	7	9062
	Negative	343	4080	15	4438
	Neutral	35	25	1440	1500

Table 8. Positive sentiment confusion matrix

Actual Class		Positive	Non-Positive	Total
	Positive	8900	162	9062
	Non-Positive	378	5560	5938
				15000

Table 9. Negative sentiment confusion matrix

Actual Class		Negative	Non-Negative	Total
	Negative	4080	358	4438
	Non-Negative	180	10382	10562
				15000

Table 10. Neutral sentiment confusion matrix

Actual Class		Neutral	Non-Neutral	Total
	Neutral	1440	60	1500
	Non-Neutral	22	13478	13500
				15000

The binary classifier' accuracy is evaluated by (Eq. 5)[43]:

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN} \quad 5$$

Applying Eq. 5 to data of Tables 6-8 now demonstrates the accuracy regarding negative comments achieving (96.41%), positive comments achieving (96.4%), and neutral comments achieving (99.4%). Additionally, with the use of Eq. 6[43], the classifier's average per-class effectiveness value—also known as its average accuracy—is determined. The average accuracy as a result was (97.4%).

$$\text{Average Accuracy} = \frac{\sum_{i=1}^{I} \frac{TP_i + TN_i}{TP_i + FN_i + FP_i + TN_i}}{I} \quad 6$$

In which, l represent the total number of classes. Average error rate, or per-class classification error average, was computed by Eq. 7 [43] and came to (2.57%).

$$\text{Average Error Rate} = \frac{\sum_{i=1}^{I} \frac{FP_i + FN_i}{TP_i + FN_i + FP_i + TN_i}}{I} \quad 7$$

By using Eq. 8 [43], the precision computation is determined. It determines the average per-class agreement between classification model and human assessments, which came to roughly 95.37 %.

$$\text{Average Precision} = \frac{\sum_{i=1}^{I} \frac{TP_i}{TP_i + FN_i}}{I} \quad 8$$

Applying Eq. 9 results in the recall computation being calculated [43]. It represents the average level of per-class agreement between classification model and human judgment. It got as high as (96.6%).

$$\text{Average Recall} = \frac{\sum_{i=1}^{I} \frac{TP_{ii}}{TP_i + FN_i}}{I} \quad 9$$

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Through using hybrid sentiment analysis regarding consumer comments on Facebook pages of the centers, the evaluation of Food items Facebook for Iraqi Food products social media. Table11 displays results.

Table 11. The results of health-care centers assessment

Positive Sentiment Range	Negative Sentiment Range	Assessments
Greater than 90%	Less than 5%	Excellent
Greater than 80%	Less than 10%	Very Good
Greater than 70%	Less than 15%	Good
Greater than 60%	Less than 20%	Medium
Greater than 50%	Less than 25%	Accept
Less than 50%	Greater than 25%	Poor

Applying the aforementioned rules to 12 Iraqi food products. Facebook finds that 2 businesses have received exceptional reviews, 2 businesses have received very good reviews, 3 businesses have received good reviews, 2 businesses have received medium reviews, 2 businesses have received acceptable reviews, and 1 business has received a poor review. Fig. 4 illustrates the chart of 12 Iraqi food product companies' assessment.

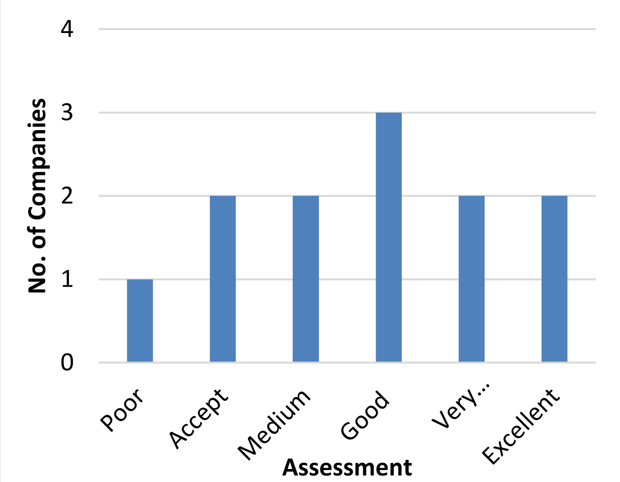

Figure 4. Iraqi Food Products Centers Assessment on the Facebook Using RST

By the trials that have been conducted and testing classification development, it has been discovered that RST has been the optimal method since it works to identify the best relations between text terms by upper and lower bounds. The lower and upper boundaries in RST might explore the best aspects of the text by the use of lexicon.

Conclusion

Customers from Iraq use Arabic and an Iraqi dialect to convey their opinions. Since they work with actual data, sentiment analysis models that are applied to the Iraqi dialect offer more advantages when compared to others. In the dialect of Iraq, terms can be broken down into double or single words to convey both negative and positive sentiment. The proposal comes with a complete Iraqi dialect lexicon that includes both double and single words for all expected terms. The limitations of lexicon-based sentiment analysis prevent it from producing results that can be trusted. The proposal used the specified lexicon to categorize the texts that were collected, and after that sentiment analysis depending on ML were used to improve the results. RST, SVM, RF and NB were four machine learning classification techniques that were used. RST, which has excellent advantages for categorized data, produced the best results when put to comparison with the other three. Despite the many advantages, SVM and RF are unable to match the accuracy of RST. Due to the fact that such analysis requires semantic features to get outcomes that are perfectly accurate and suited to reality.

Authors' Declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images that are not ours, have been included with the necessary permission for re-publication, which is attached to the manuscript.
- The author has signed an animal welfare statement.
- No animal studies are present in the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee at the Middle Technical University.

Authors' Contribution Statement

R. S. A. participated in designing the study, acquisition and analysis of data. S. M. A participated in the interpretation and conception of the study. A. T. S. participated in revision and proofreading of the manuscript. All the authors contribute in drafting the manuscript, reading and approving the manuscript.

References

1. AL-Mashhsdany AK, Ahmed SA.Textual analysis applications: subject review. J Univ Anbar Pure Sci. 2022; 12(3): 71-83. https://doi.org/10.37652/juaps.2022.171861.
2. AL-Mashhadany AK, N Hamood D, Sadiq Al-Obaidi AT, K Al-Mashhsdany W. Extracting numerical data from unstructured Arabic texts (ENAT). Indones J Electr Eng Comput Sci . 2021; 21(3): 1759-70. https://doi.org/10.11591/ijeecs.v21.i3.pp1759-1770.
3. AL-Bakri NF, Yonan JananF, Sadiq AT. Tourism companies assessment via social media using sentiment analysis. Baghdad Sci J. 2022; 19(2): 422-429. https://doi.org/10.21123/bsj.2022.19.2.0422.
4. Thorat M, Guide N F. Review Paper on Sentiment Analysis for Hindi Language. Int J Eng Sci Technol. 2022; 8(1): 51367–51396. https://doi.org/10.1007/s11042-023-17537-6 .
5. Ahmed HM, Javed Awan M, Khan NS, Yasin A, Faisal Shehzad HM. Sentiment analysis of online food reviews using big data analytics. Reviews using Big Data Analytics. Elementary Education Online (EEO). 2021; 20(2): 827-836.
6. Al-Mashhadany AK, Sadiq AT, Ali SM, Ahmed A. Healthcare assessment for beauty centers using hybrid sentiment analysis. Indones J Electr Eng Comput Sci. 2022; 28(2): 890-897. https://doi.org/10.11591/ijeecs.v28.i2.pp890-897
7. Gohil S, Vuik S, Darzi A. Sentiment analysis of health care tweets: review of the methods used. JMIR Public Health Surveill. 2018; 4(2): e43 https://doi.org/10.2196/publichealth.5789.
8. Sajid A, Awais M, Amir Mehmood MA, Batool S, Shahzad A, Zafar A. Patient's feedback platform for quality of services via ”free text analysis” in healthcare industry. Emitter Int J Eng Technol. 2020; 8(2): 316-25. https://doi.org/10.24003/emitter.v8i2.502.
9. Reyes CN, Arcega VG, Flores JM, Manez CJ, Sinday FJ, Tan JK, et al. An Analysis of the Satisfaction of Healthcare Workers on the Hazard Compensation in both private and public healthcare institutions during the COVID-19 pandemic in Metro Manila. Int J Appl Sci Eng. 2021; 1(2): 1-22.
10. Tian S, Yang W, Le Grange JML, Wang P, Huang W, Ye Z. Smart healthcare: making medical care more intelligent. Glob Heal J. 2019; 3(3): 62-5. https://doi.org/10.1016/j.glohj.2019.07.001.
11. Huchegowda R. Review on artificial intelligence and applications in healthcare. NEURO Open. 2019; 6(1): 1-4. https://doi.org/10.17140/NOJ-6-e010.
12. Mustafa J. Hadi, Ayad R. Abbas, Osamah Y. Fadhil. A Novel Gravity Optimization Algorithm for Extractive Arabic Text Summarization. Baghdad Sci J. 2024; 21(2): 537-547. http://dx.doi.org/10.21123/bsj.2023.7731.
13. Ramírez-Tinoco FJ, Alor-Hernández G, Sánchez-Cervantes JL, Salas-Zárate MDP, Valencia-García R. Use of sentiment analysis techniques in healthcare domain. Current Trends in Semantic Web Technologies: Theory and Practice. 2019; 189-212, https://doi.org/10.1007/978-3-030-06149-4_8.
14. Garouani, M, Kharroubi J. Towards a new lexicon-based features vector for sentiment analysis: application to Moroccan Arabic tweets. Advances in Information, Communication and Cybersecurity: Proceedings of ICI2C'21. 2022: 67-76, https://doi.org/10.1007/978-3-030-91738-8_7.
15. Aloqaily A, Al-Hassan M, Salah K, Elshqeirat B. Almashagbah, M., Al Hussein Bin Abdullah P. Sentiment analysis for arabic tweets datasets: Lexicon-based and machine learning approaches. J Theor Appl Inf Technol. 2020; 98(4): 612-623.
16. Duwairi RM, Ahmed NA, Al-Rifai SY. Detecting sentiment embedded in Arabic social media-a lexicon-based approach. J Intell Fuzzy Syst. 2015; 29(1): 107-17. https://doi.org/10.3233/IFS-151574.
17. Mustafa HH, Mohamed A, Elzanfaly DS. An enhanced approach for Arabic sentiment analysis. Int J Artif Intell Appl. 2017; 8(5): 1-14. https://doi.org/10.5121/ijaia.2017.8501.
18. Machová K, Mikula M, Gao X, Mach M. Lexicon-based sentiment analysis using the particle swarm optimization. Electronics. 2020; 9(8): 1317. https://doi.org/10.3390/electronics9081317 .
19. Taj S, Shaikh BB, Fatemah Meghji AF. Sentiment analysis of news articles: A lexicon based approach. international conference on computing, mathematics and engineering technologies (iCoMET). 2019; p. 1-5. https://doi.org/10.1109/ICOMET.2019.8673428.
20. Ismail R, Omer M, Tabir M, Mahadi N, Amin I. Sentiment analysis for Arabic dialect using supervised learning. J Electr Electron Eng

(ICCCEEE). International Conference on Computer, Control; 2018. p. 1-6. https://doi.org/doi: 10.1109/ICCCEEE.2018.8515862.
21. Hawalah A. A framework for Arabic sentiment analysis using machine learning classifiers. J Theor Appl Inf Techno. 2019.
22. Abo MEM, Idris N, Mahmud R, Qazi A, Hashem IAT, Maitama JZ et al. A multi-criteria approach for Arabic dialect sentiment analysis for online reviews: exploiting optimal machine learning algorithm selection. Sustainability. 2021; 13(18): 10018. https://doi.org/10.3390/su131810018.
23. Rasheed SS, Sadiq AT. Assessment of service departments in the governorates through social media comments. Iraqi J. Com. Comm. Cont. Sys. Eng. (IJCCCE). 2021; 21(2): 132-42. https://doi.org/https://doi.org/10.33103/uot.ijccce.21.2.10 .
24. Greaves F, Ramirez-Cano D, Millett C, Darzi A, Donaldson L. Use of sentiment analysis for capturing patient experience from free-text comments posted online. J Med Internet Res. 2013; 15(11): e239. https://doi.org/10.2196/jmir.2721.
25. Abualigah L, Alfar HE, Shehab M, Hussein AMA. Sentiment Analysis in Healthcare: A Brief Review. In: Recent Advances in NLP: The Case of Arabic Language. Studies in Computational Intelligence, Springer.. 2020; 874: 129–141. https://doi.org/10.1007/978-3-030-34614-0_7
26. Yadav S, Ekbal A, Saha S, Bhattacharyya P. Medical sentiment analysis using social media: towards building a patient assisted system. In: Proceedings of the eleventh international conference on language resources and evaluation; 2018. p. 2790-7
27. M. Al-Ayyoub, A.A. Khamaiseh, Y. Jararweh, M.N. Al-Kabi, A comprehensive survey of Arabic sentiment analysis. Inf. Process. Manag. 2019; 56(2): 320–342. https://doi.org/10.1016/j.ipm.2018.07.006
28. Almagrabi, A. O., Ahmad, S. Sentiment analysis system for classification of patient-generated health reviews using rough set theory and machine learning technique. J Med Imaging Health Info. 2020; 10(10): 2361-2368. https://doi.org/10.1166/jmihi.2020.3188
29. Chan CC, Liszka KJ. Application of rough set theory to sentiment analysis of microblog data. Rough Sets and Intelligent Systems-Professor Zdzisaw Pawlak in Memoriam: 2013; 2: 185-202, https://doi.org/10.1007/978-3-642-30341-8_10.
30. Azzi S, Gagnon S, Ramirez A, Richards G. Healthcare applications of artificial intelligence and analytics: a review and proposed framework. Appl Sci. 2020; 10(18): 6553-6573 https://doi.org/10.3390/app10186553.
31. Araque O, Zhu G, Iglesias CA. A semantic similarity-based perspective of affect lexicons for sentiment analysis. Knowl Based Syst. 2019; 165: 346-59. https://doi.org/10.1016/j.knosys.2018.12.005.
32. Krishna Kishore P, Prathima K, Eswari DS, Goud KS. Bidirectional LSTM-Based Sentiment Analysis of Context-Sensitive Lexicon for Imbalanced Text. Intelligent System Design: Proceedings of INDIA 2022. p. 283-297. https://doi.org/10.1007/978-981-19-4863-3_27
33. Khoo CS, Johnkhan SB. Lexicon-based sentiment analysis: comparative evaluation of six sentiment lexicons. J Inf Sci. 2018; 4(4): 491-511. https://doi.org/10.1177/0165551517703514.
34. Gavin, M. Is there a text in my data? (Part 1): On counting words. Journal of Cultural Analytics (JCA). 2020; 5(1): 1-24. https://doi.org/10.22148/001c.11830 .
35. Turney PD, Littman ML. Measuring praise and criticism: inference of semantic orientation from association. ACM Trans Inf Syst. 2003; 21(4): 315-46. https://doi.org/10.1145/944012.944013.
36. ElSahar H, El-Beltagy SR. Building large Arabic multi-domain resources for sentiment analysis. International conference on intelligent text processing and computational linguistics. 2015; 23-34, https://doi.org/10.1007/978-3-319-18117-2_2.
37. Ali AT, Ahmed TS. Lexicon-based sentiment analysis for Iraqi vernacular/Arabic language using KNN, naive Bayes and rough set theory. JARDCS. 2020; 11(11): 50-55. https://doi.org/f10.5373/JARDCS/V12SP8/20202501.
38. Kang H, Yoo SJ, Han D. Senti-lexicon and improved Naive Bayes algorithms for sentiment analysis of restaurant reviews. Expert Syst Appl. 2012; 39(5): 6000-10. https://doi.org/10.1016/j.eswa.2011.11.107.
39. Dinh CWB H, Cooper M. Naive Bayes and unsupervised artificial neural nets for Cancún tourism social media data analysis. 2010. second world congress on nature and biologically inspired computing (NaBIC). Beppu, Japan, New York: IEEE Publications. p. 158-63, https://doi.org/10.1109/NABIC.2010.5716370.
40. Khanday AMUD, Khan QR, Rabani ST. Detecting textual propaganda using machine learning techniques. Baghdad Sci J. 2021; 18(1): 0199-page??. https://doi.org/10.21123/bsj.2021.18.1.0199.
41. Gregorutti B, Michel B, Saint-Pierre P. Correlation and variable importance in random forests. Statistics and Computing. Springer. 2017; 27: 659-678, https://doi.org/10.1007/s11222-016-9646-1.
42. Loh WY, Vanichsetakul N. Tree-structured classification via generalized discriminant analysis. J Am Stat Assoc. 1988; 83(403): 715-25. https://doi.org/10.1080/01621459.1988.10478652.
43. Indurkhya N, Damerau F J. (Eds.). Handbook of natural language processing. 2010; 2(1): 627-66.

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نموذج التقييم المبني على تعليقات فيسبوك لشركات المنتجات الغذائية باستخدام أربع طرق للتعلم الآلي مع المعجم العربي/العراقي

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الخلاصة

تزداد حاجة الناس الى الغذاء يوماً بعد يوم بسبب الزيادة السكانية الكبيرة التي حصلت للمجتمع البشري، مما أدى الى زيادة كبيرة في نشاط شركات صناعة المنتجات الغذائية في العالم. من هنا تبرز الحاجة الضرورية الى تقييم اداء شركات انتاج الغذاء. وجدنا ان افضل طريقة لتقييم اداء هذه الشركات هو عن طريق تعليقات وسائل التواصل الاجتماعي، لانها الطريقة الاحدث والاكثر شيوعاً بين الناس. في هذا البحث تم الاعتماد على تقنيات تعلم الماكنة في تقييم تعليقات المشاركين في تقييم شركات انتاج الغذاء بعد ان تم الاستعانة بمعجم مصطلحات اللغة العربية عموماً واللهجة العراقية خصوصاً، وهذه المصطلحات تخص الكلمات والتعابير الايجابية والسلبية. ومن ثم التدريب من خلال خوارزميات تعلم الماكنة. تم اختبار خوارزمية الغابة **العشوائية** (RF)، و(Naive Bayes (NB ، و Rough Set Theory (RST)، و(Support Vector Machine (SVM . أثبتت التجارب أن طريقة RST تفوقت على الثلاثة الآخرين. حيث أن طريقة (RST) حققت نسبة دقة (96.13%)، وحققت طريقة (SVM) نسبة دقة (95.75%)، حققت طريقة (RF) نسبة دقة (94.1%) وحققت طريقة (NB) نسبة دقة (87.1%).

الكلمات المفتاحية: نموذج تقييم، اللهجة العراقية، تعليقات الفيس بوك، انتاج الغذاء، تعلم الماكنة.