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Assessment of Delivery Companies Based on Lexicon Using Intelligence Techniques and Arabic WordNet

Mohamad Ab. Saleh[1]*, Ali Hadi Hasan[2], Ahmed T. Sadiq[3]

[1]*Banking and Financial Department, College of Economic and Administration, Al Iraqia University, Baghdad, Iraq*

[2] *College of Information Technology, University of Babylon, Babylon, Iraq*

[3] *Department of Computer Science, University of Technology, Baghdad, Iraq*

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Abstract:

In recent years, the activities of delivery companies have surged due to various factors, including epidemics, cost-effectiveness, the ease of placing orders, and urban congestion. This paper presents a model for evaluating the performance of delivery companies by analyzing comments available on social media. Assessing a company's performance based on feedback from corporate customers provides a valuable indicator for predicting its future success or failure. The main strength of this paper lies in utilizing a simple dictionary of Arabic and Iraqi dialect words to describe essential terms and leveraging Arab WordNet to enhance the quality of description words extracted from comments. The accuracy values for the four machine learning models used in our study are as follows: Rough Set Theory (RST) 97.5%, Support Vector Machine (SVM) 96.7%, Random Forest (RF) 94.3%, and Naïve Bayes (NB) 89.2%. The results demonstrate that the RST algorithm outperforms the other algorithms in terms of accuracy, representation, and recall.

Keywords: Arabic WordNet, Delivery companies, Lexicon-based, Sentiment Analysis, Machine Learning, NLP, Social media Data.

تقييم شركات التوصيل على أساس المعجم باستعمال تقنيات الذكاء و الوورد نت العربية

محمد عبدالرضا صالح[1], علي هادي حسن[2], احمد طارق صادق[3]

[1] قسم العلوم المالية و المصرفية, كلية الإدارة والاقتصاد, الجامعة العراقية, بغداد, العراق

[2] كلية تكنولوجيا المعلومات, جامعة بابل, بابل, العراق

[3] قسم علوم الحاسبات, الجامعة التكنولوجية, بغداد, العراق

الخلاصة

في السنوات الأخيرة، ارتفعت أنشطة شركات التوصيل بسبب عوامل مختلفة، بما في ذلك الأوبئة، التكلفة العالية، وسهولة تقديم الطلبات، والازدحام الحضري. يقدم هذا البحث نموذجا لتقييم أداء شركات التوصيل من خلال تحليل التعليقات المتاحة على وسائل التواصل الاجتماعي. إن تقييم أداء الشركة بناءً على تعليقات العملاء من الشركات يوفر مؤشرًا قيمًا للتنبؤ بنجاحها أو فشلها في المستقبل. تكمن القوة الرئيسية لهذا البحث في استعمال قاموس بسيط للكلمات باللهجة العربية والعراقية لوصف المصطلحات الأساسية والاستفادة من WordNet العربي لتحسين جودة الكلمات الوصفية المستخرجة من التعليقات. قيم الدقة لنماذج التعلم الآلي

* Email: mohamad.abd.saleh@aliraqia.edu.iq

الأربعة المستعملة في دراستنا هي كما يلي: (Rough Set Theory RST 97.5% ، Support Vector Machine SVM 96.7% ، Random Forest RF 94.3% ، Naïve Bayes NB 89.2%).
أظهرت النتائج أن خوارزمية RST تتفوق على الخوارزميات الأخرى من حيث الدقة والتمثيل والتذكر.

1. Introduction

Artificial intelligence techniques have ushered in a new reality in the digital world, especially within social media sites. These technologies are being harnessed to align with technological advancements, enhance competitiveness, and play a pivotal role. Consequently, a significant portion of the public is increasingly relying on these technologies for various purposes, including accessing news [1], acquiring information [2], enjoying entertainment [3], and facilitating shopping [4]. Furthermore, they provide unique opportunities to gauge the general sentiments of diverse individuals and ideas [5].

One of the critical issues is effective access to the emotions of social media users. This involves understanding what they follow and the reactions they express to extract valuable insights [6]. The influence of artificial intelligence is particularly profound on social media platforms, as it enables swift and accurate analysis, yielding innovative solutions, improving navigation, and expediting knowledge sharing. This is especially relevant in the context of the fourth industrial revolution, which is expected to introduce new technologies to these platforms [7].

The integration of artificial intelligence into social media sites has raised various concerns. These include the extent to which the public embraces AI-driven decisions regarding content publishing and the provision of services traditionally associated with human interaction. Users' satisfaction with interacting with AI, its problem-solving capabilities, and concerns about data security and privacy have also emerged. Additionally, there are apprehensions about the use of personal data for promotional purposes within the realm of big data, which is integral to AI applications for processing information and predicting public behavior and preferences [8].

Two main perspectives divide expert opinions on the use of artificial intelligence on social media platforms. Some experts believe that AI enhances performance and enables more efficient and rapid communication with individuals. Conversely, another group expresses concerns about the potential negative repercussions of AI, fearing that it might negatively impact the performance of social networking sites or result in the automation of routine tasks, potentially lacking creativity and human spirit [9].

The aim of this paper is to present an intelligent approach to evaluating the performance of delivery companies based on reviewers' comments on social media. Our approach is based on several intelligent techniques, such as natural language processing (NLP), text mining, and machine learning methods. All of these are based on Arabic WordNet, a lexicon tool with a simple lexicon for Iraqi dialect words. This paper will depict the important related works and the concept of sentiment analysis. In addition to the details of the proposed work, show the experimental results, discussion and conclusion.

2. Related works

In the following, we will review a series of papers authored by researchers who employed various techniques to extract emotions from Arabic texts:
1- Social media platforms have steadily developed in recent decades, and as a result, there is a growing need to analyze users' feelings based on what they publish on these platforms. This

analysis relies on inferring users' feelings from the text they receive. The issue of analyzing the user's feelings is a very glamorous area due to the provision of many personal services to the user, in addition to improving his experience working on various communication platforms. The researchers chose the Twitter platform because it is one of the most popular platforms for social communication and has many users around the world in multiple languages and cultures. As a result, it is possible to reach a lot of highly important and diverse information, which is considered the main pillar in strengthening the issue of decision-making. In this research, texts and symbols were studied, and emotions associated with them were extracted by analyzing tweets and comments written in Arabic during the 2018 FIFA World Cup. Thousands of tweets were used to reach a logical analysis of texts and symbols and to reach a conclusion associated with the feelings. The study concluded that the texts and emojis are complementary to each other as a support for reaching emotional orientation, and one cannot be relied upon without the other separately [10],[11].

2- The researchers created descriptive groups to ensure the quality and performance of the much-needed sentiment analysis of social media users. The aforementioned groups are very important in many natural language processing operations, such as translation and text classification. As a standard test, feedback from users of the platforms is used to measure the accuracy of the rating. In this research, publications available on the Facebook platform written in Arabic, which were summarized and used as Arabic groups, were used. The aforementioned groups are distinguished in that they do not depend on spelling or grammatical rules but rather depend on what is written in the Arabic dialect. The group was categorized into five categories (positive, negative, dual, neutral and spam). In addition to the foregoing, the researchers replaced the manual signs with words and phrases related to the content of the sign for use in the dictionary-based workbook [12].

3- Arabic-language social networks offer a rich source of user opinions in the form of comments. While there has been significant research on opinion mining in English-language content, the analysis of Arabic text has been comparatively limited due to the complexities of the language and the shortage of tools for extracting emotions from Arabic text. Dialects, such as the local Saudi dialect, exacerbate these challenges. This study concentrates on sentiment analysis concerning unemployment in the Kingdom of Saudi Arabia, particularly in the local dialect. It tackles these challenges by preprocessing the text and employing supervised machine learning to ascertain the positivity or negativity of sentiments. The results demonstrate effective emotion classification, particularly in determining the polarity of sentiments, which can be instrumental in enhancing sentiment analysis quality [13].
4- Recent times have witnessed an increase in comments from social media users regarding the services offered by various companies. This has prompted companies to take these comments seriously in order to gauge customer satisfaction with their products and services. In this paper, researchers propose several techniques to extract customer sentiments from their written comments. Analyzing Arabic text poses multiple challenges; one of the most prominent is the extraction of the word's root. The researchers have devised a framework for categorizing Arabic comments and classifying customer sentiments into three categories: positive, negative, and neutral. After training the framework on various examples and testing its effectiveness, they collected and studied the results [14].

3. Sentiment Analysis

In recent decades, electronic commerce has developed steadily, accompanied by the emergence of many social networks, which have allowed people to review companies efficiently and compare the products, services and prices provided by them. Facebook, perhaps the most widely used social media in Iraq, serves as a long-term tool for reaching out, as it features a dedicated company page where users can post and receive comments. In this paper, we will rely on Facebook as a source for fetching text comments for users and using artificial intelligence techniques to know users' feelings towards the services provided by the delivery companies, which is used as basic data to assess companies. User comments are a realistic, direct expression of the user (satisfied, dissatisfied, or neutral) and they are important information for delivery companies that are constantly striving to develop their services to gain customer satisfaction [15].

The idea of extracting information from texts has gained the attention of researchers. This information is divided into two main parts, where the first is the facts, which are direct expressions of an issue or an object or their characteristics, which we can understand directly, while the second is the opinions, which are self-expressions that describe the feelings or assessments of people towards an issue or an object or their characteristics, which often need treatments for the purpose of understanding and distinguishing them. In addition to the above, the polarity of people's feelings has been classified into positive and negative [16].

4. Proposed Approach

This section aims to clarify the key steps of the proposed approach. The basic target of the approach is to extract feelings from the text comments on the social networking sites of the people who benefit from the services provided by the delivery companies. The process of reaching the aforementioned feelings is crucial to reaching conclusions by which it is possible to judge the success or failure of the services provided by companies to customers and thus determine the future of the company in terms of its rise or fall in the business world. Figure 1 below shows the basic steps of the proposed system:

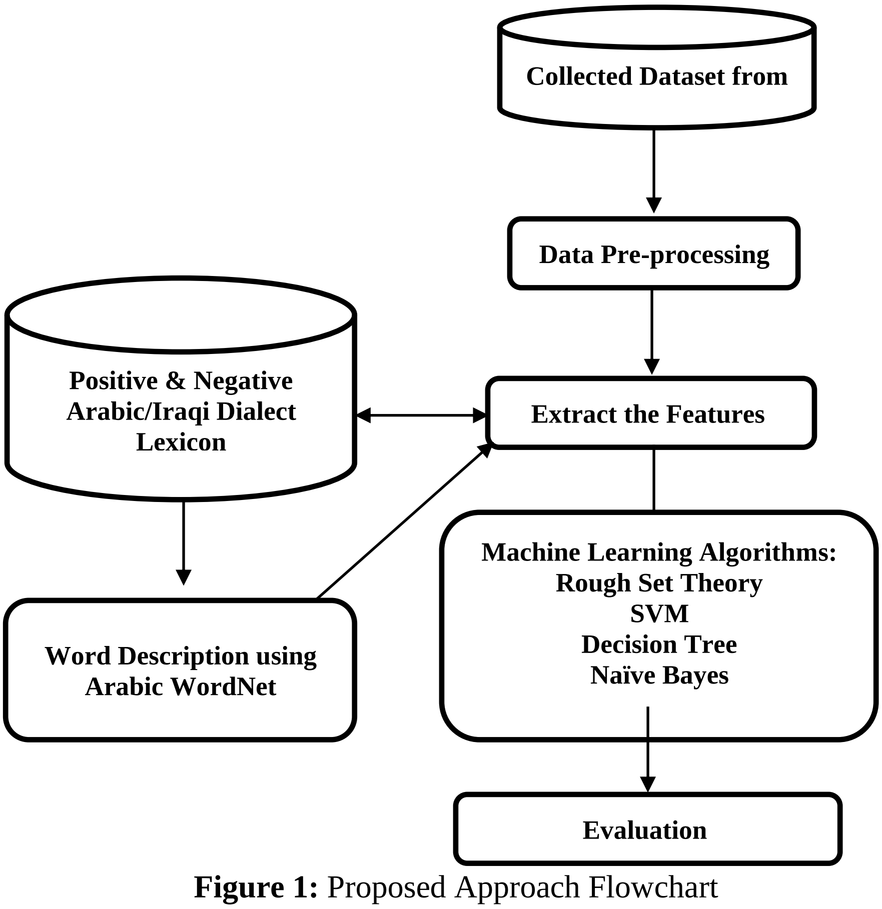

Figure 1: Proposed Approach Flowchart

In addition, the below algorithm represents the main stages of our approach:

```
Input: Collected dataset from social media (Data);
        Positive & Negative Arabic/Iraqi Dialect Lexicon (Arab_Iraqi_Lexicon);
        WordNet;
        StopWords;
Output: Companies Assessment;
Begin
        Make a tokenization to the Data;
        Remove stop-words from Data depend on StopWords;
        Make a light stemming;
        Make a training stage using Rough Set Theory depend on Arab_Iraqi_Lexicon and
Arabic WordNet features;
        Make a training stage using Random Forest Algorithm depend on labeled Data;
        Make a training stage using Naïve Bayes Theory depend on labeled Data, Arabic
WordNet features and Arab_Iraqi_Lexicon;
        Make a training stage using Support Vector Machine depend on labeled Data;
For each machine learning results Do
        For each Delivery Company Do
                        Apply the rules in Table (8) to the result;
                        Determine the Delivery Company assessment;
                End for
        End for
End.
```

4.1 Collected Data Set

The proposed system collects the comments of people who benefit from delivery companies' services on the Facebook platform as its first step. Most of the time, people write their comments on a new advertisement from the company or based on their personal experiences, opinions, and/or feelings. Based on the foregoing, agents' comments are an important source for evaluating the services provided by the delivery companies. First of all, the comments of the agents' are collected and then filtered to keep comments that relate to services and ignore others. It has been noted that most of the agents' comments relate to the services provided by the companies. Most of the remaining comments, which represent a small percentage of the total number of comments, will be related to the people working in the companies, the location of the companies, or the companies' working hours.

In our work, the data was collected based on reviewers' comments on Facebook for 10 Iraqi delivery companies'. These comments include both Arabic sentences and Iraqi dialect words. Table 1 shows some of these comments.

Table 1: Sample of Arabic/Iraqi Dialect Reviewers' Comments

موفقين دوماً
بالتوفيق حبيبي
هو أنتو على التلفون ما تجاوبون غير تعبانين
أرقى شركة صار لي سنتين وياكم
بالتوفيق ان شاء الله تعالى دووووم ملتزمين
افضل شركة بس لو عدكم عروض يكون احسن
عمي كقيلك الله كله جذب، مواعيدكم تعبانه

4.2 **Data Pre-processing**

At this stage, comments are received, which are verbatim texts that will go through several transformational stages (i.e., removing stop-words, tokenization and stemming) to prepare them for the next step.

4.3 Positive & Negative Arabic/Iraqi Lexicon

The existence of a lexicon of positive and negative Arabic words added a lot to the proposed model. In order to increase the strength of the proposed model, positive and negative Iraqi dialect words were added to the Arabic language lexicon. This addition will enhance the strength of the results because most of those who write on social networking sites and networks are the ones who use the colloquial dialect and not the classical language. Hence, the addition of Iraqi dialect words was necessary to increase the efficiency of the proposed model. Table 2 shows some positive and negative (1-gram and 2-gram) words in the Iraqi dialect.

Table 2: Sample of positive and negative words in the Iraqi dialect

Positive Words	Negative Words
مرتبين	تعبانين
حلوين	قشامر
كلش زين	قفاصة
بالتوفيق	طاح حظكم
دوووم ملتزمين	استفاااد
عاشت الايادي	مو خوش
سالمين	كله جذب

4.4 Using Arabic WordNet

Arabic Wordnet is a serious work that requires a lot of diligent research. Its importance stems from being a lexical source that contains much linguistic information, such as words, antonyms, synonyms and meronyms [17].

Often, words come in the comments that the system does not recognize due to insufficient training data, a lack of comprehension of the dictionary, or other reasons, and often these words are synonyms or words that have a strong relationship with dictionary words or training texts; hence, we resort to what is called a description of the words. The strength of the proposed model is its ability to extract the full description of the important words in the comment using the capabilities of Arabic WordNet. Through this description, the proposed model can search for word details and what is related to them for the purpose of linking the words and knowing whether the word has a relationship with positive or negative words. For example, in the English language, the word "good" was not present in the positive dictionary, and the system was not trained on it. When referring to its specifications in WordNet, we find that one of its synonyms is the word "well," which is considered a positive word. Another example: let us take the word "lousy." Within the linguistic definition of this word, we find the word "dirty." So the two words have the same meaning. The same is the case in the Arabic language using Arabic WordNet. Therefore, the description of words provides us with valuable insights into their definitions, synonyms, and opposites. All of this gives strength to the proposed model by knowing the types of new words in the new comments. By using the Arabic WordNet, we can obtain the following details of the word (i.e., definition, synonym, hypernym, hyponym and antonym).

4.5 Extract the features

The most important feature of our proposal is its reliance on several characteristics in the text classification process. In addition to the words of the classical Arabic language, the Iraqi dialect dictionary was adopted, which contains most of the Iraqi dialect words that indicate positive and negative. These characteristics gave us the ability to distinguish the text in the Arabic language and the Iraqi dialect together. In order to add a stronger feature, the word description was retrieved using WordNet, as it gives us complete information about the word, such as:

- Definition: What does that word mean, and what are you talking about?
- Synonym: They are two words that have the same meaning but are in different texts, such as (جاء) and (أتى), where in this case, they are linked by a relationship called synonymous. These words fall into the same group in WordNet.
- Hypernym: They are two words that have different meaning and different text, such as (طيور) and (حمامة), where the first one is the hypernym, which represents the broader category, while the second one is the hyponym, which represents a subordinate category.
- Hyponym: They are two words that have different meanings and different texts, such as (النمل) and (الحشرات), where the first one is the hyponym, which represents the subordinate category, while the second one is the hypernym, which represents a broader category.
- Meronymy: They are two words that have different meaning and different text, such as (أوراق)and ,(شجرة) where the first one is the meronym, which represents a part or a component of the second one, which is called a holonym.

The use of the aforementioned word description adds a lot of information about the original word and its branches, and if there is a word that is synonymous, similar, derived from it, or branched from it, the proposed system will know that, which gives it power and a wide area of knowledge about important words [18].

The most important advantage of using word description through WordNet is that if the original word (positive or negative) does not exist, it searches for it in the specifications it extracts from WordNet, and this means that it searches in the largest possible area in the information of the word in question through definition, synonym, hypernym, Hyponym and meronym. For example, the word (جيد) has synonyms such as (رائع, جميل, مثالي); therefore, it is not necessary that it come in the form of (جيد) [19].

4.6 Machine learning algorithms

In this section, we will present four of the most important algorithms in the field of machine learning that are applied in our work:

1- Rough Set Theory: This algorithm is used in intelligent systems that do not have accurate information. The approximate group is a formulaic approximation of a conventional fragile group by formulating two groups containing the upper and lower estimates of the original one. The main concept of this algorithm is the inability to distinguish between two things based on their main characteristics [20].

2- Support Vector Machine: It is a widely used classification method in intelligent systems for problems that need binary classification. This method looks for hyperplanes that stabilize the decision limits, sorting the data into two main categories. The distance between hyperplanes is maximized by solving the quadratic programming problem. An algorithm is computationally excellent even in nonlinear problems that require a lot of time to execute the kernel trick [21], [22].

3- This algorithm is one of the important methods used in machine learning models to solve problems related to regression and classification. Overall, as an aggregate model, it has very low predictive error and variance. In addition to the foregoing, they are characterized by a highly positive ability to learn and improve their performance in a dramatic way [23], [24].

4- This algorithm is widely used as a classification tool in statistical models based on mathematical hypotheses. This method is based on probabilistic classification based mainly on Bayes' theory. Its main method of work depends on the characteristics of the object and ignores the state of interdependence between these characteristics, which may lead to error [25],[26].

5. Results obtained from experiments and discussion

The suggested model underwent an experimentation phase using Facebook comments that were gathered from 10 delivery companies in Iraq. The dataset, which is outlined in Table 3, was carefully curated by the researchers, who examined the Facebook pages of these 10 companies. They sifted through 35 posts from each page and selected 35 comments per post after filtering out any unrelated content. This process yielded a total of 21,400 sentences from all comments.

Table 3: Statistical characteristics of the dataset

Pages	Posts	Comments	Sentences
10	350	10500	21400

The first step involved the application of a lexicon-based sentiment analysis method that utilized Arabic WordNet features, which was carried out on a total of 10,500 comments. Following this, four machine learning classification techniques were employed, namely Rough Set Theory (RST), Support Vector Machine (SVM), Random Forest (RF), and Naïve Bayes (NB). Figure 2 presents the accuracy rates of these algorithms in performing sentiment analysis on the dataset, with the RST algorithm achieving the highest accuracy rate at 97.5%. The practical application of the algorithms showed varying percentages, with SVM achieving a 96.7% accuracy rate, RF achieving 94.3%, and NB achieving 89.2%. From the foregoing, we can clearly distinguish that the RST algorithm is the most accurate among all other algorithms.

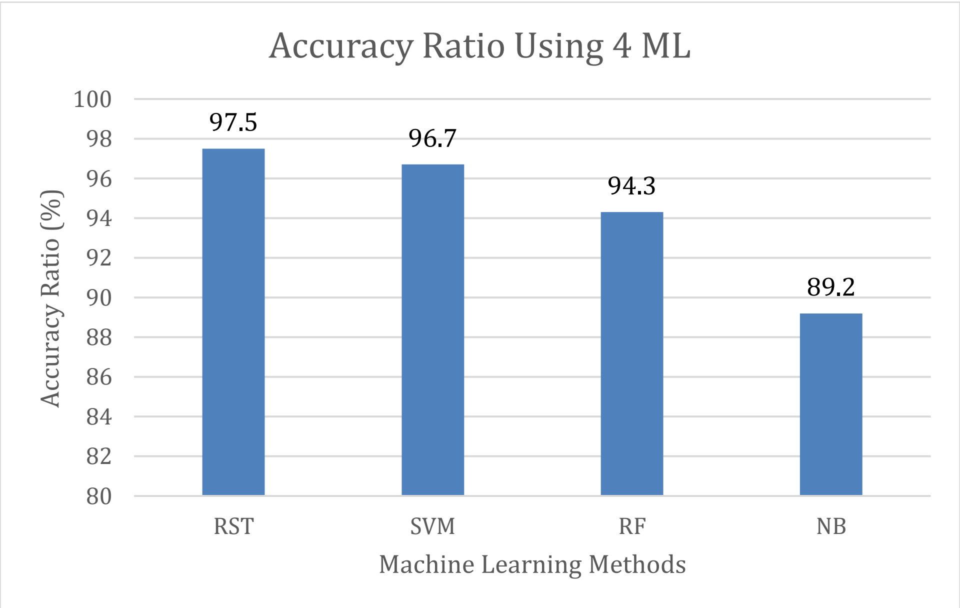

Figure 2: Sentiment Analysis Accuracy

Table 4 presents a breakdown of the confusion matrix results for the three categories (neutral, positive, and negative) and for ten thousand and five hundred comments using the RST method.

Table 4: The sentiment classification of 10,500 comments using the RST algorithm

		Predicated Class			Total
		Positive	Negative	Neutral	
Actual Class	Positive	8234	185	21	8440
	Negative	82	1525	18	1625
	Neutral	16	14	405	435
					10500

Tables 5, 6, and 7 provide further information regarding the sentiment classification of the 10,500 comments. These tables display the detailed confusion matrices for comments categorized as those conveying positivity, those conveying negativity and those falling in the middle with a neutral sentiment, respectively.

Table 5: Positive Sentiment Matrix of Confusion

		Anticipated category		Total
		Positive	Non-Positive	
Actual Class	Positive	8234	206	8440
	Non-Positive	98	1962	2060
				10500

Table 6: Matrix of Confusion for Unfavorable Sentiment

		Anticipated category		Total
		Negative	Non-Negative	
Actual Class	Negative	1525	100	1625
	Non-Negative	199	8676	8875
				10500

Table 7: Neutral Sentiment Confusion Matrix

		Anticipated category		Total
		Neutral	Non- Neutral	
Actual Class	Neutral	405	30	435
	Non- Neutral	39	10026	10065
				10500

The accuracy of the binary classifier is determined through the use of Eq. 1 [23]:

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

By utilizing Equation 1 and analyzing the data presented in Tables 2, 3, and 4, it has been determined that the accuracy rate for positive comments is 97.55%, while the accuracy rate for negative and neutral comments is 93.85% and 93.1%, respectively. Additionally, the average accuracy rate of the classifier, which is computed using Eq. 2 [23], was found to be 94.83%.

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

Here, the variable I represents the total number of classes.

The average error rate, which refers to the average per-class classification error, is determined through the calculation shown by Eq. 3 [23]. It reached 0.97%.

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

The precision computation is calculated by applying Eq. 4 [23]. This metric computes the average level of concordance between human assessment and the classification model on a per-class basis, resulting in an accuracy rate of approximately 94.83%.

$$\text{Average Precision} = \frac{\sum_{i=1}^{l} \frac{TP_i}{TP_i + FP_i}}{l} \quad \ldots (4)$$

The recall calculation, as determined by Eq. 5 [23], involves averaging the agreement between the classification model and human judgment on a per-class basis. This method yielded a recall rate of 92.82%.

$$\text{Average Recall} = \frac{\sum_{i=1}^{l} \frac{TP_i}{TP_i + FN_i}}{l} \quad \ldots (5)$$

This study involves the evaluation of Iraqi delivery companies through the use of a hybrid sentiment analysis approach, utilizing customer comments on their respective Facebook pages. A number of rules were proposed for evaluation through the ratio of positive and negative, which is considered the main criterion for evaluating companies through the classification of comments, and these laws are shown in Table 8.

Table 8: The outcomes of the evaluation of delivery companies

The spectrum of favorable emotions	The spectrum of adverse emotions	Evaluation
≥ 80%	None	Excellent
≥ 70% & < 80%	None	Good
≥ 60% & < 70%	*≥ 10% & < 20%*	Moderate
≥ 50% & < 60%	*≥ 20% & < 30%*	Approval
Otherwise	Otherwise	poor

The evaluation of ten Iraqi delivery companies, using the guidelines outlined in Table 8, revealed that 24% received an excellent evaluation, 44% a good evaluation, 15% a moderate evaluation, 10% an approval, and 7% a poor assessment. Figure 3 illustrates these results.

Table 9: Average Measurement Results of Rough Set Theory for 10 Delivery Companies

Average Measure	Result
Accuracy	94.83%
Error Rate	0.97%
Precision	94.83%
Recall	92.82%

Table 10: Delivery company evaluation results

Company	Positive	Negative	Neutral	Assessment
A	82%	11%	7%	Very Good
B	79%	13%	8%	Good
C	78%	12%	10%	Good
D	47%	35%	18%	Bad
E	68%	18%	14%	Medium
F	81%	9%	10%	Very Good
G	69%	16%	15%	Medium
H	78%	11%	11%	Good
I	58%	24%	18%	Acceptance
J	79%	13%	8%	Good

Implementing the aforementioned guidelines on ten Iraqi delivery companies revealed that two companies received a very good assessment, four companies received a good assessment, two companies received a moderate assessment, one company was deemed acceptable, and one company was rated poorly. Figure 3 depicts these outcomes.

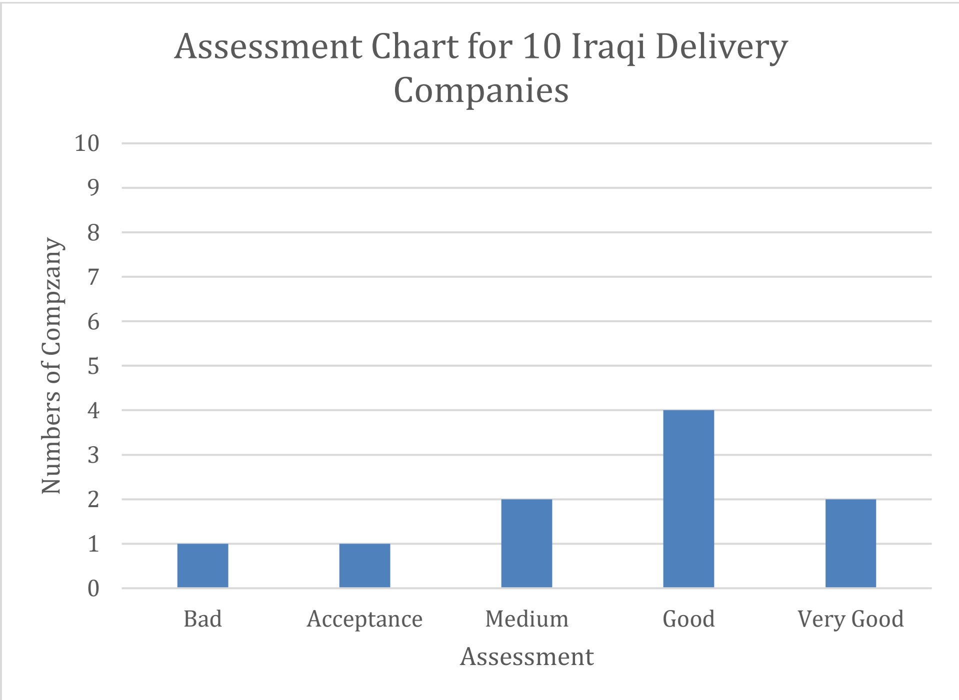

Figure 3: Iraqi Delivery Company Assessment

The evaluation results, developed specifically for this purpose, reveal that the ten companies received varying evaluations, with the majority receiving an average or higher rating. We developed the rules in Table 6 to be logical and appropriate for the evaluation process of these companies. This process involved analyzing positive and negative tendencies in Arabic and Iraqi dialect words, describing these words using Arabic WordNet, and incorporating this data into our machine learning methods.

The use of the lexicon and the information it contains about the characteristics of the word, positively or negatively, played a major role in improving the results in terms of the accuracy of the obtained results. We have utilized sentiment results from various companies to ensure an objective and valuable evaluation across multiple stages of classification.

6. CONCLUSION

The Iraqi dialect, which deals with actual data, expresses the opinions of Iraqi customers, offering certain advantages for sentiment analysis models compared to others. We can infer positive and negative feelings from individual or two-word phrases in the Iraqi vernacular. We create an appendix with an Iraqi dialect lexicon that encompasses all anticipated single- and double-word terms. However, relying solely on a sentiment analysis based on a lexicon approach may fall short of attaining precise outcomes. So, the appendix uses the provided lexicon to sort the collected documents into groups and uses four machine learning-based sentiment analysis methods (RST, SVM, RF, and NB) to improve the outcomes. Among these, RST achieved the best results due to its benefits for categorizing data. However, even RST could not reach 100% accuracy, as semantic features are required to achieve results that match reality without any error rate. The use of word descriptions found in the word net helped improve the RST algorithm's accuracy in determining positive and negative sentiment, resulting in an improvement in the evaluation process for delivery companies.

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8. Disclosure and conflict of interest

1- Conflict of Interest: The authors declare that they have no conflicts of interest.

2- We affirm that all the tables and figures included in the manuscript are our original work. Additionally, we have obtained permission for re-publication for any external figures or images used, and we have included them with the manuscript.

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