Heliyon 10 (2024) e30320

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

An analysis of customer perception using lexicon-based sentiment analysis of Arabic Texts framework

Ohud Alsemaree *, Atm S. Alam, Sukhpal Singh Gill, Steve Uhlig

School of Electronic Engineering and Computer Science, Queen Mary University of London, London, E1 4NS, UK

A B S T R A C T

Sentiment Analysis (SA) employing Natural Language Processing (NLP) is pivotal in determining the positivity and negativity of customer feedback. Although significant research in SA is focused on English texts, there is a growing demand for SA in other widely spoken languages, such as Arabic. This is predominantly due to the global reach of social media which enables users to express opinions on products in any language and, in turn, necessitates a thorough understanding of customers' perceptions of new products based on social media conversations. However, the current research studies demonstrate inadequacies in furnishing text analysis for comprehending the perceptions of Arabic customers towards coffee and coffee products. Therefore, this study proposes a comprehensive Lexicon-based Sentiment Analysis on Arabic Texts (LSAnArTe) framework applied to social media data, to understand customer perceptions of coffee, a widely consumed product in the Arabic-speaking world. The LSAnArTe Framework incorporates the existing AraSenTi dictionary, an Arabic database of sentiment scores for Arabic words, and lemmatizes unknown words using the Qalasadi open platform. It classifies each word as positive, negative or neutral before conducting sentence-level sentiment classification. Data collected from X (formerly known as Twitter, resulted in a cleaned dataset of 10,769 tweets, is used to validate the proposed framework, which is then compared with Amazon Comprehend. The dataset was annotated manually to ensure maximum accuracy and reliability in validating the proposed LSAnArTe Framework. The results revealed that the proposed LSAnArTe Framework, with an accuracy score of 93.79 %, outperformed the Amazon Comprehend tool, which had an accuracy of 51.90 %.

1. Introduction

In today's hyper-connected world, social media has become an indispensable tool for communications, information-sharing, entertainment, and so on. With the rise of platforms like Facebook, Instagram, and Twitter (rebranded under the name 'X'), people are now able to connect and engage with others from all corners of the globe, regardless of language or location. One of the most popular languages spoken worldwide is Arabic, with over 400 million speakers [1]. Resultantly, the massive number of Arabic speakers significantly impacts the online landscape, as Arabic is one of the most commonly used languages on the Internet. This includes the conversations occurring on social media platforms.

Among the various social media platforms available, Twitter stands out as one of the most widely used, with 330 million monthly active users worldwide and an average of 500 million tweets shared every day [2]. Given the scale and diversity of data available on Twitter, it has become an important source of data for research and analysis, particularly in the field of Sentiment Analysis (SA). Due to the platform's large user base and frequent interactions, researchers have access to a huge dataset that they can utilize to examine sentiment and attitude trends related to various dialogues, emotions, and demographics.

SA on social media is a challenging research area [3] as it involves parsing and interpreting vast amounts of unstructured data from diverse sources. SA is a field of research that examines how individuals feel about things, emotions, and attitudes toward entities and

* Corresponding author.
E-mail address: acw672@qmul.ac.uk (O. Alsemaree).

https://doi.org/10.1016/j.heliyon.2024.e30320
Received 15 March 2024; Received in revised form 23 April 2024; Accepted 23 April 2024
Available online 1 May 2024
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their attributes as they are conveyed in written language [4]. Businesses and organizations rely heavily on SA to understand customer perceptions towards their products or services for personalization [5]. Customer perception refers to how a customer feels about a product or a service [6]. This includes their thoughts, emotions, and opinions related to a product or service. It is crucial for any business and organisation to understand their customers' perceptions, i.e., to gain a comprehensive understanding of their customers' perception and knowledge regarding their products and services [7].

Customer perception analysis using Arabic text is a very under-studied area because of the scarcity of datasets annotated in Arabic for the task. Despite the existence of millions of reviews for several products, services, and events, this work will pay keen attention to food-related products like coffee. The primary source of reviews for the datasets to be used will be social media platforms using tweets from people who tried the coffee and provided their views about it. The customers' perceptions of the coffee products are predicted as either positive, negative or neutral sentiment classifications at the sentence level.

Saudi Arabia holds the top position for Twitter usage in the Arab world, highlighting its significant digital engagement [8]. However, there's a noticeable gap in research efforts aimed at intelligently classifying reviews via SA through Arabic text, especially when considering the nuances of the Saudi dialect. This combination of widespread social media use and the lack of advanced analytical tools presents both a challenge and an opportunity for developing more sophisticated language processing technologies in the region. Hence, we propose a Lexicon-based Sentiment Analysis on Arabic Texts (LSAnArTe Framework), which integrates the existing Arabic Sentiment (AraSenti) database and Arabic lemmatization tool, Qalasadi [9], to create Arabic lexicons. Lexicons are the collection of tokens where each token is assigned a predefined score which indicates the neutral, positive, and negative nature of the text [10]. This study focuses on lexicon-based SA due to its ease of use and effectiveness [11].

Furthermore, it is also prudent to mention that in this paper we will be comparing the results with Amazon Comprehend, which is an NLP service that can analyse and extract insights from text data [12]. We have used Amazon Comprehend on the same dataset we have used for validating our proposed model. In addition, Amazon Comprehend is a service provided by Amazon Web Services (AWS). AWS services provide more than 200 services with complete functionality from data centres across the world, including working in natural language processing (NLP) technologies to perform different analyses such as SA [12].

The study aims to develop a system for analyzing the feelings of the comments drawn from the Twitter platform to understand customer perceptions. Furthermore, this paper focuses on the creation of LSAnArTe by using the AraSenTi dictionary in the field of foodstuffs to help companies and institutions adopt the classification of products in more or fewer sales and requests. Consequently, the study findings will help to identify more accurate quality products that are available or not depending on the reviews, purchasing decisions, using techniques and algorithms for prospecting via customer SA. It will also help save time and money by providing companies with accurate performance statistics and enabling them to understand the customer's perception and marketing requirements.

This research presents LSAnArTe, a new framework for sentence-level Arabic text analysis, and the Customer Perception Lexicon, a framework for precise customer sentiment interpretation. The following are the key contributions of this paper.

- A novel framework named LSAnArTe is proposed that primarily targets sentence-level Arabic text analysis and is applicable across various domains; it is particularly beneficial for café shops to understand customer perceptions of their product.
- The LSAnArTe Framework proves exceptionally advantageous for trading companies aiming to gain insights into product demand and predictive analytics. By harvesting data from social media and focusing on Arabic language reviews, it produces a refined dataset encompassing more than 10,769 tweets.
- The Framework leverages the AraSenTi dictionary, a valuable resource comprising informal Arabic texts sourced from Twitter. Moreover, the work incorporates the Arabic classics library of morphological analysis (Qalasadi), which significantly enhances the accuracy and comprehensiveness of the lexical analysis model.
- The proposed framework is validated and compared with the Amazon Comprehend tool to evaluate the accuracy of the model.

This paper is organized as follows. Section 2 reviews the related works. In Section 3, the methodology of our approach is discussed. Performance and Evaluations are detailed in section 4. Section 5 highlights the Results and Discussion. Finally, Section 6 provides the conclusion and the future work.

2. Related work

Lexicon sentiment analysis plays a crucial role in understanding and analyzing the sentiment expressed in text data, such as reviews, social media posts, and customer feedback.

There are two approaches conducted for constructing lexicons; namely: dictionary-based lexicons and corpus-based lexicons [13]. This study focuses on using a Lexicon-based approach because of its ease of use. Compared to corpus-based approaches, which analyse vast amounts of text data to extract sentiment patterns, syntax-based dictionaries are easier to create and require less computing power because they already have lists of words and the sentiment ratings that go along with them.

Given the complexity of Arabic morphology and the difficulties associated with sentiment annotation in corpora, lexicon-based dictionaries are especially well-suited for Arabic sentiment analysis since they are better able to convey the subtleties of sentiment in Arabic language. Thus, lexicon-based technique provides a more straightforward and resource-efficient solution without compromising accuracy for Arabic sentiment identification [14].

Sentiment analysis within the Arabic linguistic domain, particularly through lexicon-based approaches, remains notably underrepresented in natural language processing research. This discrepancy highlights a significant oversight, given the extensive body of SA literature available for the English language, which does not directly translate to the complexities and unique characteristics of Arabic. Such a gap is particularly pronounced considering the global prevalence of Arabic, spoken by over 400 million individuals, and its significant presence on social media platforms [15].

This section discusses the existing literature focused on employing lexicons for the SA of Arabic texts. It examines the scope of these studies, including their focus areas, the highest levels of accuracy achieved, the methodologies employed for lexicon creation and naming, and the capacity for these dictionaries to complement or incorporate additional lexicons. A few scholars, as detailed in Table 1, have suggested engaging proposals for developing lexicon-based Sentiment Analysis systems for Arabic. Nonetheless, there is still room for further investigation to explore the potential of these approaches with regard to improving the accuracy and efficiency of Sentiment Analysis in Arabic.

Abdul-Mageed et al. [16] work introduced the SAMAR system, a significant advancement in SA for Arabic social media. Their approach integrated both Modern Standard Arabic (MSA) and dialectal Arabic, offering a comprehensive language processing solution. However, notable limitations exist within their methodology. Firstly, the absence of a supporting dictionary for lexicon-based SA represents a gap in their approach. Additionally, the focus on the combination of the general Egyptian language and classical Arabic may not adequately represent the linguistic diversity across Arabic-speaking regions. Consequently, the generalisability of their findings in comparison to other Arabic-speaking communities with distinct linguistic and cultural backgrounds is limited. Moreover, the study's scope lacked specificity in terms of topics covered and sample size, posing further challenges in extrapolating its conclusions. These limitations underscore the need for continued research to address the complexities of SA in diverse Arabic contexts.

Authors [17] undertook a study to enhance the lexicon-based approach for SA in Arabic. Their paper outlined a meticulous procedure for constructing such an approach. The study utilized Twitter and Yahoo! Maktoob as data sources for a specific study sample which could be useful in creating a specialized lexicon for arts and politics, albeit divergent from the study's primary focus. Despite this, the research underscores the importance of tailored dictionaries to facilitate nuanced SA across various domains. However, although the authors leveraged annotation data automatically, the investigation centered on the Jordanian dialect and classical Arabic, and it omitted the utilization of dictionaries to bolster the lexicon's robustness. These findings highlight both the advancements and limitations in the current approaches to Arabic SA and emphasize the ongoing need for methodological refinement and domain-specific lexicon development.

Guellil et al. [18] conducted a study that focused on the identification of Arabic dialects through unsupervised learning based on a lexicon. Specifically, the application case studied was the Algerian dialect. The study aimed to address the problem of dialect identification in an unsupervised manner, leveraging the use of a lexicon and corpus resources. The researchers improved the lexicon by adding the Algerian dialect, which had previously been used in analyzing other dialects such as the Iraqi and Tunisian dialects. The study was limited to one source in social media; namely Facebook, and the data coverage was within narrow limits of 1000 messages. The researchers used the Java program for data analysis, unlike previous studies that employed the Python program. The field of study was general and not focused on a specific topic. The researchers took advantage of a previously built lexicon that had been enriched to improve the Algerian dialect dictionary. The study was carried out on a website{www.jeeran.com} and it was diverse in the subjects of restaurants, hotels, and clinics.

The scope of the study [19] was general, and not bound to any particular domain. The authors suggested that this approach can be of benefit in defining a non-specific general lexicon. The focus of the study was on the Arabic language, particularly the colloquial Palestinian and Jordanian dialects. The data coverage was substantial, consisting of 15100 reviews. The authors employed an automatic tagging method to extract labels. It is noteworthy that the study did not make use of a dictionary to support the lexicon-creation process. Moreover, Almosawi et al. [17], pursued a lexicon-based approach geared towards SA of student feedback. The objective was to discern the polarity of feedback gathered from students through lexical-based SA. Data collection involved the distribution of an online questionnaire among students, yielding a dataset encompassing two language varieties: the Iraqi dialect of southern Iraq and the modern Arabic language (MAL).

Another study conducted research work which delved into Arab text analysis, specifically focusing on SA of the Emirati dialect [18]. This research aimed to construct a lexicon-based SA model tailored for the Instagram platform which was capable of accurately assessing sentiment in Emirati dialect comments through manual annotation. The study's domain was specific to language and

Table 1
A comparative review of related research on Lexicon-based SA in the Arabic language.

No	Annotation	Data Source	Focus	Dictionary	Language	Best Result
[13]	Manually	Synchronous chat, Twitter, Web Discussion Fora, and Wikipedia Talk Pages	General	–	MSA Egyptian dialect	71.28 %
[14]	Automatic	Twitter and Yahoo! Maktoob	Politics and art	–	MSA, Jordanian dialects	70.05 %
[15]	Automatic	Facebook	General	Another lexicon	Algerian dialect	63.75 %
[16]	Automatic	Social Media	Restaurants, hotels, clinics	–	MSA Palestinian Jordanian dialect	90 %
[17]	Automatically	Twitter	General	–	Moroccan dialect	70.05 %
[18]	Manually	Instagram	General	–	Emirati dialect	80 %
LSAnArTe (our model)	**Manually**	**Twitter**	**Customer perception**	**AraSenTi**	**MSA,Saudidialects**	**93.79 %**

concentrated on the nuances of the Emirati dialect, thereby positioning it as a specialized investigation. Leveraging a lexicon-based approach, the authors employed a predefined set of positive and negative words to categorize comments as positive, negative, or neutral.

Table 1 summarizes the outcomes of previous studies that used lexicon-based SA in Arabic. It can be observed that annotation occurs either automatically or manually within those papers. Data sources were collected from various social media sources such as Facebook, Twitter, Instagram and others. Most of the data focuses on general data; there is a lack of customer perception which could have a massive impact on companies and organizations in relation to product personalization. The dictionary utilized for those studies may have not been declared. Finally, the benchmark results vary from 70 % to 90 % depending on the correlation and complexity of the given data.

3. Methodology

The methodology section of this paper presents the framework and processes behind the Lexicon SA on Arabic Texts Based on Social Media (LSAnArTe), a novel model designed to capture and analyse customer sentiments from Arabic language reviews on Twitter. This model specifically targets the coffee sector, aiming to glean insights into customer perceptions through the systematic analysis of social media content.

The LSAnArTe model leverages a lexicon-based approach, utilizing a self-constructed and manually annotated lexicon that includes approximately 10,769 sentences. This extensive lexicon serves as the foundation for SA, enabling the identification and categorization of sentiments expressed in online reviews about coffee products. The workflow of the LSAnArTe model is detailed in Fig. 1, which illustrates the step-by-step process from data collection through SA to the final sentiment classification. This visualisation aids in understanding the comprehensive approach taken to analyse sentiments in Arabic text related to coffee, emphasizing the model's reliance on the specialized lexicon and its analytical capabilities. The detail of each step is considered in this section.

3.1. Data preparation

In this section, we present the preparation of the data within three stages: data collection, data annotation and data pre-processing. The details of each of these are presented in this section.

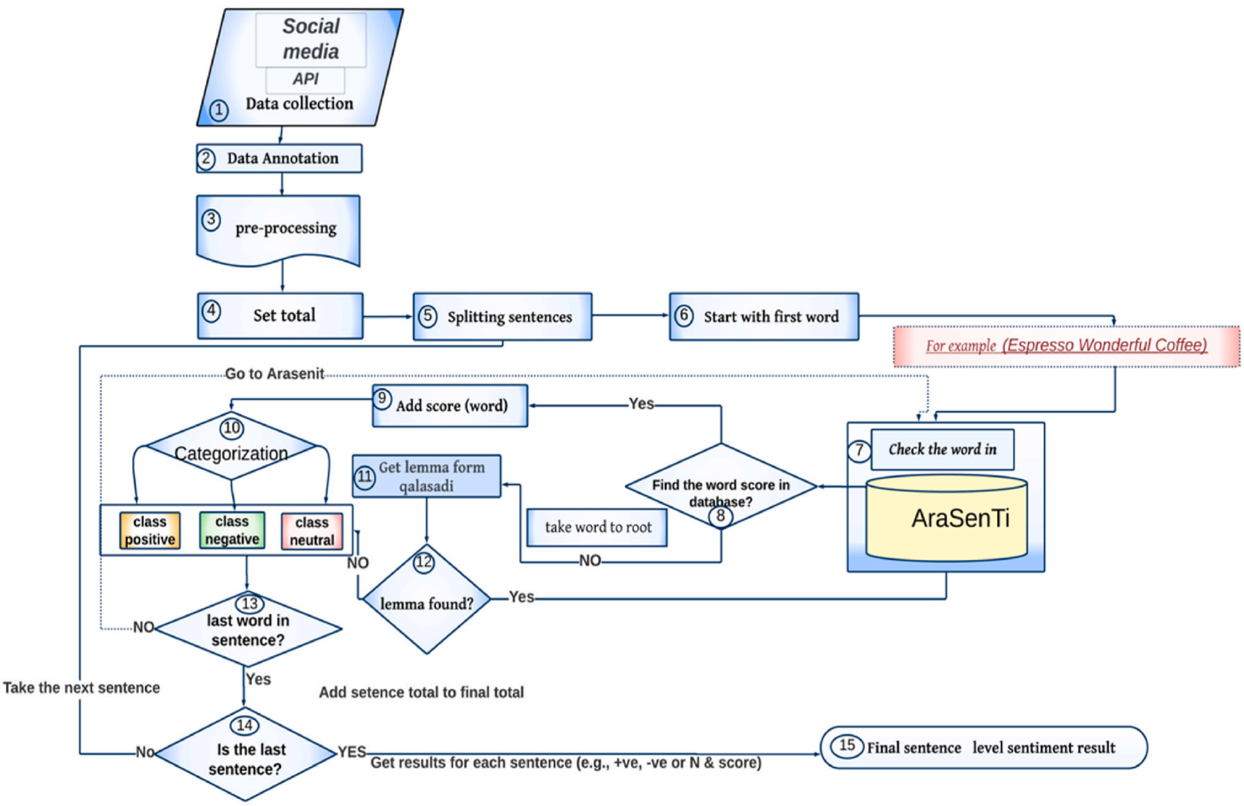

Fig. 1. Flowchart for LSAnArTe: Lexicon sentiment analysis on Arabic texts from social media.

3.1.1. Data collection

Twitter was chosen for this study primarily due to its significant popularity in Saudi Arabia, boasting the highest usage levels in the Arab world. This popularity has not only facilitated extensive digital engagement among Saudis but has also positioned Twitter as a focal point of study within the Saudi research community [20]. Furthermore, the country's high internet penetration rate has transformed Twitter into a key platform for cultural, social, and political engagement, making it a vital arena for public expression and debate [21]. Another advantage of Twitter is its provision of an Application Programming Interface (API), which simplifies the retrieval of public tweets for analysis [22].

The platform's limit of 140 characters per tweet eases the processing and analysis of data, making it ideal for prototype implementation and proof-of-concept purposes. The brevity of tweets allows researchers to efficiently collect and analyse large volumes of data, facilitating the testing and demonstration of new sentiment analysis (SA) concepts or prototypes [23]. Focusing on social data generated from Twitter and utilizing the API, approximately 12,000 tweets were gathered and analysed at the sentence level. The collected data comprised tweets predominantly related to a range of coffee suppliers within the Saudi market.

3.1.2. Data annotation

The manual approach was utilized for data annotation, categorizing each tweet as (positive +1, negative-1, or neutral,0). After pre-processing the data, labeling the data is the next crucial step. However, this step can be challenging due to the absence of a universally agreed model or theory for labeling [24]. The process of assigning labels to the data requires careful consideration and subjective interpretation based on the specific goals and objectives of the study. It is a fact that, in the absence of an established model or theory, researchers often resort to developing their own annotation criteria or guidelines. This involves defining categories or sentiments based on the research context and conducting a manual annotation process.

Manual labelling entails human annotators reviewing and categorizing the pre-processed data based on predefined criteria. While this approach allows for flexibility and customization, it also introduces subjectivity and potential inter-annotator variability. Researchers must ensure transparency and consistency in the Annotation process by providing clear guidelines to annotators and performing quality checks to maintain reliability. Labelling can be carried out both by manually crowd-sourcing or automatically [25]. While developing the proposed Lexicon-based SA on Arabic Texts LSAnArTe Framework, manual annotation was used for the sentences to mark them (positive, negative, or neutral). Manual annotation is indeed a labour-intensive, time-consuming, and expensive method because it depends on humans to check labels [26]; however, it provides high-quality Arabic sentiment lexicons. The lexicons manually generated are considered more accurate than sentiment lexicons that are generated automatically.

3.1.3. Pre-processing

The dataset was refined through pre-processing, resulting in a total of 10,769 tweets. The preprocessing of the dataset involved a number of processes to improve the text in preparation for analysis. Initially, linkages were eliminated by removing any Uniform Resource Locator (URL). After that, all punctuation was removed from the text. In order to preserve consistency with the Arabic alphabet, non-Arabic characters were also removed from the dataset. Hashtags in tweets were separated for additional examination, and user mentions in the pattern @username were eliminated. The tweets' emojis were taken out and given additional thought. Using the Camel Tools library, the text was standardized to ensure consistency throughout the dataset. Particular characters were also normalized, such as Alef and Alef Marbouta. Furthermore, Tokenization of the text was also done, which divided it up into distinct parts like words or sentences. In order to minimize redundancy and improve the efficiency of the analytic process, duplicate retweets were finally eliminated from the dataset.

Fig. 2 illustrates how the data cleansing procedure greatly improves text clarity by removing extraneous elements such as links, hashtags, and emojis, which can obscure or misrepresent the words' intended meaning. Therefore, purifying the data is essential for accurately capturing sentiments and categorizing comments as positive, negative, or neutral. Fig. 3 then provides a concise summary of this text data processing stage.

	Tweet	Tweet_cleaned	Hash_tags	Emojis	Tweet_len
0	ايس امريكانو دانكن يداقس اي مشروب بالعالم	ايس امريكانو دانكن يداقس مشروب بالعالم			6
2	رحت اخذ قهوه من دانكن والحساب ١٠ ريال وجيت بحاسب طلعت مرفوضه والكاشير يصيح	رحت اخذ قهوه دانكن والحساب وجيت بحاسب طلعت مرفوضه والكاشير يصيح			11
3	https://t.co/D7UzXeq8q6 😭 😭 بيفتحون دانكن عندنا	بيفتحون دانكن عندنا		[😭]	3
4	حرفيا لي ساعة طالب دونات بس!!! وماوصلت تسهيلون ولا كيف ياهنقر اتوقع هاذي اخر مره اطلب منكم @HungerStation دانكن	حرفيا ساعة طالب دونات وماوصلت تسهيلون ياهنقر اتوقع هاذي اخر مره اطلب منكم دانكن			14
9	جرب اطلب من تطبيق غير مرسول وهنقرستشين وجاهز وصل وتويو ونعناع داشقز\n\nفجاه وماخلصتي إسمه (مستر\n\n.ازهلها السعوديه عسير جزان بيشه الطائف الخبر الليك دانكن تبوك خميس مطاعم الرياض 😍 🍦 🍩 ..(Mo11) و كوبون اول طلب\n اوعدك انه بيعجبك عن تجربه\n\n مندوب)	فجاه وماخلصتي جرب اطلب تطبيق مرسول وهنقرستشين وجاهز وصل وتويو ونعناع داشقز ازهلها السعوديه عسير جزان بيشه الطائف الخبر الليك دانكن تبوك Mo مطاعم الرياض اسمه مستر مندوب اوعدك بيعجبك تجربه كوبون طلب		[😍, 🍩, 🍦]	33
12	✅ دانكن القبيله\n ❎ دانكن الحي	دانكن الحي دانكن القبيله		[❎, ✅]	4
21	😂 اخذت دونات الحين من دانكن ماقي الا بكره @4ri1l1	اخذت دونات الحين دانكن ماقي بكره		[😂]	6
22	💔 انتظر قهوه دانكن تجي بس ماجات	انتظر قهوه دانكن تجي ماجات		[💔]	5

Fig. 2. Examples of original tweets and their processed equivalents.

Fig. 3. Summary of the text data processing stage.

3.1.4. *Sentence scoring and splitting*

To guarantee data accuracy and readiness, two essential preliminary measures are carried out prior to using the AraSenTi lexicon for sentiment analysis. In order to generate a baseline sentiment value, each sentence in the database is first initialized with a neutral score of 0. For example, Sentence 1, which consists of the words, Word1, Word2, Word3, and Word4, has the following initial score computed: Word1 + Word2 + Word3 + Word4 = 0 is the score for Sentence 1. The sentences are then broken up into individual words for additional processing. This careful planning is essential to enabling correct assessment of the emotional tone expressed in each sentence and to support successful sentiment anaysis.

3.2. *Word weight in each sentence*

At this stage, we focus on word weight within each sentence, the process encompasses several key stages: utilizing the AraSenTi Dictionary, scoring in AraSenTi, classification of sentiment (positive, negative, neutral), and lemmatization using Qalasadi.

3.2.1. *Scoring in AraSenTi*

The process starts with the first word of the sentence; for example, if 'Espresso is a wonderful coffee', is the sentence, the first word will be 'Espresso'. The word score is checked against the AraSenTi dictionary to find its score. There can be two outcomes: (1) the word is found, or (2) no word is found. In the case of outcome (1), proceed to step 9; for outcome (2), proceed to step 11.

In terms of finding the word (1), add a score to it which then follows by classifying the class based on the given score. On the other hand, with word (2), if the word has not been detected, calculate the lemma of the root. If the lemma is found it goes back to step 7 to get a score, if not it is automatically classified as neutral in step 10. The classification occurs based on a comparison of the given score with the threshold as shown in 3.10. The AraSenTi database is accessed to determine each word's sentiment score. Word-level classification is facilitated by retrieving and appending the score of a word if it is contained in the AraSenTi database.

3.2.2. *AraSenti-PMI for word-level SA*

In the construction of the LSAnArTe, the AraSenti-PMI dictionary method was employed as shown in Algorithm 1 [27]. This method involves measuring the relationship between pairs of words by calculating the point-wise mutual information (PMI) measure for all words present in the positive and negative datasets of tweets [28].

The PMI measure assesses the statistical association between two words by considering their co-occurrence frequency and comparing it to the expected frequency of their co-occurrence under independence (see (1)). It quantifies the strength of the association between words, indicating how often they occur together compared to what would be expected by chance.

$$PMI\ (W, pos) = log_2 \frac{freq\ (w, pos) * N}{freq(w) * freq(pos)} \tag{1}$$

The frequency of the term (w) in the positive tweets, $freq(w,pos)$, the frequency of the word w in the dataset is given by $freq(w)$, the number of tokens in the positive tweets is represented by $freq(pos)$, and (N) is the total number of tokens in the dataset. In the same method, it uses PMI (w, neg), and the PMI of the word connected to negative tweets is determined.

$$Sentiment\ Score\ (w) = PMI\ (w, pos) - PMI(w, neg) \tag{2}$$

A high sentiment score influences the classification as shown in (2). If a word is not found in the negative dataset, it doesn't mean its sentiment is positive, and vice versa. So, we use Equation (1) to calculate the sentiment score for such words. We use $PMI(w,pos)$ for words only in positive tweets and $PMI(w,neg)$ for words only in negative tweets.

3.2.3. *Qalasadi for lemmatization*

If a word is not present in AraSenTi, Qalasadi (an Arabic lemmatizer), is used to convert words into their fundamental form. The Qalasadi Arabic Morphological Analyses Library [9] is designed to support the Arabic language and aims to map any Arabic word to its root or base form. This process of lemmatization assists in normalizing and standardizing the language for various text analysis tasks. This procedure guarantees thorough coverage and precise sentiment analysis, even for words which are not explicitly listed in the AraSenTi database. To get the overall sentiment score at the sentence level, the sentiment score of each word is then added together. This systematic approach guarantees an in-depth and accurate sentiment analysis, augmenting the robustness and dependability of the outcomes attained.

Fig. 4 shows, for example, to get a lemma from Qalasadi "take word to root", in this case for the word wonderful lemma = wonder.

So instead of the actual word, the root of the word is used.

If the lemma is found or marked as YES, the root word is checked against the AraSenTi dictionary to get the word score and it is then added to the sentence-level total score. Next, get the classification for that word and for this word wonderful, it is positive. If the lemma is not found in Qalasadi, then we give the word (=0) score and classify it as neutral. In the case of coffee, it is neutral. The integration of lemmatization using the Qalasadi Arabic Morphological Analyses library contributes to improving the accuracy and comprehensiveness of the LSAnArTe Framework for Arabic text. It enables the identification of sentiment-related words even when they appear in different inflected or derived forms [29]. This will be elaborated further in the Performance Evaluation section.

3.2.4. Word -based sentiment analysis categorization

Based on the final score obtained from AraSenti a, each word is classified as positive, negative, or neutral as previously mentioned. For example, the first word 'Espresso' is classified as neutral. After that, repeat the process for the second word (wonderful), and so on. In case the word under processing is not found, then lemmatization converts words into their root form.

Algorithm 1: LSANARTE Framework

```
Input: Collected Tweets dataset (D)
Output: Sentiment label for each sentence
Begin
Splitting (S) into Words (W)
Initialise W =0
For W(i) in which i:1 to the number of words in a Sentence
If W(i) in AraSenti then
  Get Sentiment Score for that W(i) as Ws(i)
Else if Wi is not in Arasenti then
  Search for lemma (root) for W(i) using Qalasadi
    If the root is found
        Search for AraSenti for updated W(i)
        Get a Sentiment score for Ws(i)
     Else if W(i) is not available in Qalsadi then
      Sentiment Score Ws(i)=0
    End if
End if
If Ws(i) >= +0.2, then % This for providing information for elaboration
  Classify Positive Word
Else if Ws(i)==0 then
  Classify Neutral Word
Else if Ws(i)<= -0.2 then
  Classify Negative Word
End If
End for
Compute Score for the sentence: Ss=Ss = ∑_{i=1}^{Number of Words} Ws(i)
 If Ss >= 0.2, then % This system assumed/adapted 20% tolerance.
  Classify Positive Sentence
Else if Ss==0 then
  Classify Neutral Sentence
Else if Ss<= -0.2 then
  Classify Negative Sentence
End if
```

Our goal is to find a set of relevant sentiment labels for each sentence (s) within the Dataset (D) as shown in the Algorithm. in Which each s consists of L-numbers of Words (w). The location of each word is located as i. Then calculating the score for each wi within every sentence is conducted through AraSenTi as previously mentioned in Fig. 1. Algorithm 1 details the steps for calculating the score of each Wi, Word index of i within a sentence (s). The utilized symbol within the algorithm is presented in Table 2.

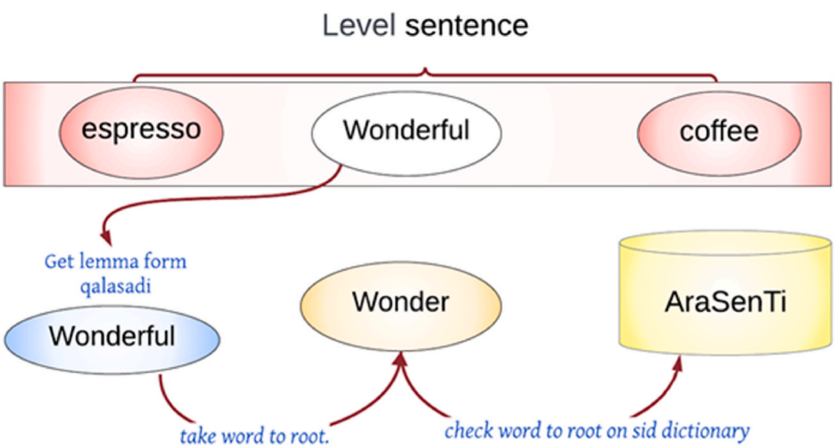

Fig. 4. The root Extraction process.

3.3. Sentence-level scoring

The sentence-level scoring process involves concatenating scores for each sentence and the final sentence-level sentiment result.

3.3.1. Score concatenation for each sentence

The score concatenation for each sentence is achieved using the following steps.

1) If the last word of the sentence is encountered, then add the sentence total to calculate the total.
2) If there are other words, repeat the steps mentioned above till the end of the sentence is reached.
3) If the last sentence is detected (YES), get the results for each sentence (positive, negative, neutral),
4) If (NO), select the next sentence.

3.3.2. Final sentence level sentiment result

The sentiment score of all words in the tweet was summed up using a specific threshold to classify the data into either positive, negative or natural. The threshold is set by examining various settings including those recommended in the literature (Kiritchenko et al., 2014). The best results were obtained when the threshold values are set to 0.2 as positive scores, −0.2 as negative scores and 0 as neutral scores. Therefore, the sentiment classification is performed by comparing the scores of words in each sentence. The criteria for sentence classification are provided below.

- If the score is greater than 0.2, the sentence is classified as positive (assigned a value of 1).
- If the score is less than −0.2, the sentence is classified as negative (assigned a value of −1).
- All remaining words are classified as neutral (assigned a value of 0).

4. Performance evaluation

In this section, we outline the performance evaluation for SA of Arabic using a Lexicon approach, encompassing steps such as preparation, dataset collection, data annotation, pre-processing, leveraging the AraSenTi dictionary, employing Qalasadi for lemmatization, and finally, evaluation.

4.1. Dataset collection

The data is collected in this paper using Twitter's API and employing Python and libraries such as Tweepy to request access to users' tweets and their information. These were collected at the sentence level. The collected tweets focused primarily on various coffee providers in the Saudi market, using hashtag keywords for different labels of coffee companies; including Dunkin Coffee; Saudi Costa; Starbucks Coffee; Barneys Coffee; Tim Hortons Coffee; half a Million Coffee; dr. cafe coffee; and overdose Coffee.

The tweets were archived in dictionaries containing details such as text, username, location, and timestamp. For systematic data management, information pertaining to each company was organized into distinct files in pickle format. These files were subsequently converted to a CSV file format to improve accessibility and simplify analysis. This study's data collection process involved extracting tweets from Twitter, resulting in a compilation of 12,255 tweets over the research period.

4.2. Data annotation

After carefully and manually annotating the classification of the dictionary, as previously discussed, three gradients are provided for the annotation, which are positive '+1', negative '-1' and neutral '0'. The example occurrence of the manual annotation of the mentioned classification is presented in Table 3.

4.3. Pre-processing

After refining the dataset with a Python script to ensure its suitability for analysis, we retained 10,769 tweets in order to examine customer perceptions expressed on social media in Arabic relating to the coffee products shows the Sentiment Distribution of Arabic Coffee Product Tweets after pre-processing in terms of negative (4529), positive (5203), and neutral (1037).

Table 2
List of symbols and their definition.

Symbol	Definition
D	Tweets dataset
w_i	Word index of $_i$
s	Sentence
$w_{\,i}(s)$	Sentiment score for word $_i$
$\Sigma_i^L w_i^{(L)}$	Summation of sentiment score of the sentence of ($_L$ words)

Table 3
Manually annotated LSAnArTe SAR example tweets.

Annotation	Tweet in Arabic	Tweet in English
+1	احب القهوة العربية	I love Arabic coffee
−1	القهوة طعمها سي	The coffee tastes bad
0	جربوا قهوة فلات وايت	Try flat white coffee

4.4. *AraSenTi dictionary*

The AraSenti-PMI dictionary method serves as a valuable approach to developing a lexicon-based SA model, enabling the capture of sentiment associations between words and enhancing the accuracy of Sentiment Analysis results. By applying the AraSenti-PMI dictionary method, the lexicon for SA is constructed based on the calculated PMI scores between word pairs. Words with high positive PMI scores are indicative of positive sentiment, while words with high negative PMI scores signify negative sentiment. This method allows for the identification of sentiment-bearing words and the establishment of a lexicon that can be utilized for SA [30].

Table 4 presents the analysis of the positive Arabic words within the dictionary and reveals their significant impact on the sentiment of coffee-related comments. Words like "حلى، حلو، لذيذ ، رائع" not only convey positive sentiments, but also endorse and advocate coffee as being a desirable product. This positive lexicon contributes to a favorable impression of coffee among consumers, whilst also highlighting attributes that enhance its appeal. Conversely, Table 5 presents a selection of negative words from the dictionary, such as "سي، خايس، مر ، اسوء", which are associated with adverse emotions towards coffee.

These negative terms suggest dissatisfaction or shortcomings, detracting the perception of coffee being considered as an enjoyable product. This dichotomy between positive and negative word influences underscores the pivotal role of specific lexical choices in shaping consumer sentiment and perceptions of coffee, as evidenced by the data presented. Neutrality marked with a score of zero shows no evaluative value.

4.5. *Qalasadi for lemmatization*

Our research capitalizes on the Qalasadi library's advanced lemmatization capabilities to navigate the intricate linguistic features of Arabic, particularly for SA in coffee product reviews. The morphological diversity of Arabic means that words can appear in numerous forms, thereby complicating recognition by standard sentiment dictionaries. By reducing words to their lemma forms, the Qalasadi library ensures uniform analysis across variable textual expressions, a step which is crucial for accurate sentiment mapping and categorization. For instance, Fig. 4 shows various forms of "wonderful" are consolidated under the root "wonder", allowing for precise sentiment assignment based on the dictionary entries. This approach not only bolsters the accuracy of sentiment detection in Arabic texts, but also sets a precedent for handling linguistic complexity in Sentiment Analysis. This provides further evidence of the potential of our methodology in broader research contexts.

Upon analysing customer feedback on a coffee product, we observed distinct lexical choices that align with positive, negative, and neutral sentiments. Fig. 5 shows words such as "لذيذ - يجنن- رائع" "Nice," "Delicious", "Wonderful" and "Lovely", were prevalent in positive comments, thereby confirming the consumers' approval and appreciation of the product flavour and overall quality. Conversely, negative remarks frequently employed descriptors. Fig. 6 shows words such as "مر- سي", "bitter", "overpriced", and "bad", highlighting specific dissatisfaction facets and unmet expectations. Fig. 7 shows Neutral feedback often included terms like "مر- عادي -معتاد" "average", "normal" and "okay" indicating neither a distinctly positive nor negative perception of the coffee product. The identification of these sentiment-specific words is crucial for nuanced SA, as they provide a foundation for a comprehensive understanding of consumer attitudes towards the product.

4.6. *Evaluation*

This section evaluates the performance of the LSAnArTe Framework (Lexicon-based Sentiment Analysis on Arabic Texts) using metrics such as accuracy, precision, recall, and F1 Score, to determine the model with the most successful prediction in analyzing sentiment within comments on coffee products [31]. These metrics offer quantitative measures of the Framework's classification performance in SA tasks. These metrics include Accuracy (Acc), Precision (P), Recall (R), and F1-score (F1). They are calculated based on the confusion matrix metrics True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN) [29].

Accuracy: is the total number of correct results over the total number of predictions as shown in Equation (3).

Table 4
Positive Arabic words in the sentiment dictionary.

Word	Translated Words	Sentiment Value	Valuing Words in the AraSenti Dictionary
احلي	Nice	Positive	0.696
حلو	Lovely	Positive	0.648
لذيذ	Delicious	Positive	0.69
رائع	Wonderful	Positive	0.697

Table 5
Negative Arabic words in the sentiment dictionary.

Word	Translated words	Sentiment Value	Valuing Words in the AraSenti Dictionary
خايس	Bad	Negative	−1.38
مر	Bitter	Negative	−0.88
اسوء	Worse	Negative	−2.06

Fig. 5. Positive words visualisation.

Fig. 6. Negative words visualisation.

Fig. 7. Negative words visualisation.

$$Accuracy = \frac{TP + FN}{TP + TN + FP + FN} \tag{3}$$

Precision: is the ratio of how a model can better extract true positive (TP) results compared to the total number of positive results. It is used to minimize false positives as shown in Equation (4):

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

Recall: is the ratio of how a model can better extract true positive (TP) results compared to the maximum number of positive results that can be returned. It is used to minimize the false negatives as shown in Equation (5):

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

F1 - Score: $F1$ - Score ($F1$) measurement is a measure of the accuracy of the test, which is then divided into the recall and precision as shown in Equation (6).

$$F1 - Score = \frac{2\ X\ Recall\ X\ Precision}{Recall + Precision} \tag{6}$$

5. Results and Discussion

This section evaluates and discusses the LSAnArTe Framework's effectiveness in predicting customer sentiments towards coffee products and contrasts these findings with those obtained from the "Amazon Comprehend" service. To conduct this comparative analysis, both methods were applied to the same dataset to ensure consistency in the evaluation. Amazon Comprehend, which processes unstructured data, was leveraged to determine whether the provided Arabic text - evaluated at the sentence level - conveys positive, negative, or neutral sentiments. The text files, specifically related to coffee SA, were uploaded to Amazon S3, a cloud-based storage service provided by AWS, for processing and analysis. After executing the necessary code to analyse the uploaded content, the outcomes were meticulously compared against those derived from the manually annotated LSAnArTe Framework.

The comparative analysis particularly focuses on the accuracy performance of both LSAnArTe and Amazon Comprehend. According to the results, which are illustrated in a subsequent Table 6, the LSAnArTe Framework significantly outperforms Amazon Comprehend, demonstrating a remarkable accuracy rate of 93 %. In contrast, Amazon Comprehends accuracy stands at 51 %. LSAnArTe demonstrates superior performance across all metrics, including precision (P), recall (R), F1 score, and accuracy (ACC). Specifically, LSAnArTe achieves higher precision and recall rates for positive (+1) and negative (−1) sentiment classes compared to Amazon Comprehend. This indicates LSAnArTe's ability to effectively identify and classify positive and negative sentiments with greater accuracy.

The LSAnArTe framework outperforms Amazon Comprehend in accuracy for all sentiment classes, indicating its overall effectiveness in SA tasks. One possible reason for LSAnArTe's superior performance could be its tailored approach to Arabic sentiment analysis, which may better capture the nuances and complexities of Arabic language usage compared to the more generalized approach of Amazon Comprehend. Additionally, LSAnArTe may utilize specialized lexicons or linguistic features optimized for Arabic sentiment analysis, further contributing to its higher accuracy and performance metrics.

This significant difference highlights the LSAnArTe Framework's superior capability in accurately classifying and understanding customer sentiments in Arabic texts related to coffee products. The enhanced performance of LSAnArTe suggests its potential as a more reliable tool for SA in specific domains, particularly when analyzing texts in the Arabic language.

This study considered a total dataset of 10,769. The data was classified into three classes: ve, 0 and +ve. This study found that both automatic and manual SA annotation techniques have benefits and limitations. By manually annotating text data with sentiment labels, human annotators are able to accurately capture minor sentiment variations and enable complex interpretations. This improves accuracy and relevance by guaranteeing high-quality annotations and allowing customization to certain domains or businesses.

The confusion matrix under examination provides a profound insight into the performance of the LSAnArTe model, a tool specifically designed for SA of customer perception regarding coffee products in the Arabic language on social media. This analysis breaks down the model's predictions into positive, neutral, and negative categories. Remarkably, LSAnArTe accurately identified 5027 instances as positive, 550 as neutral, and 4523 as negative sentiments towards coffee products, demonstrating its exceptional ability to distinguish between the diverse sentiments expressed by Arabic-speaking customers on social media platforms (see Fig. 8).

The matrix also highlights certain discrepancies between the model's predictions and the actual sentiments. It shows that LSAnArTe misclassified 6 positive sentiments as neutral and 0 as negative. Additionally, 481 neutral instances were incorrectly identified as negative, and 6 neutral instances were incorrectly classified as positive, suggesting an area for improvement in recognizing neutral opinions about coffee products among Arabic-speaking social media users (see Fig. 9).

The use of a color gradient in the matrix serves to effectively underline the distribution of predictions, with darker shades indicating a higher frequency of instances. This visual aid provides an intuitive understanding of LSAnArTe performance in accurately classifying sentiments regarding coffee products among Arabic-speaking audiences. The darkest shade, indicating 5027 instances, mostly aligns with correct predictions, confirming the overall efficacy of LSAnArTe in sentiment classification. Nonetheless, the presence of lighter shades in off-diagonal elements of the matrix points to a need for further refinement of the model, particularly in the accurate classification of neutral sentiments and in reducing misclassifications between positive and negative sentiments related to coffee products. This thorough analysis emphasizes the potential for enhancing LSAnArTe sensitivity to the subtle distinctions of sentiment, thereby improving its application in real-world assessments of customer perception of coffee products in the Arabic language on social media.

The Amazon Comprehend Confusion Matrix, applied to the sentiment analysis of Arabic language customer perceptions of coffee products on social media, presents a clear picture of its ability to classify sentiments into positive, neutral, and negative categories. The model accurately detected 2779 positive sentiments, showcasing its proficiency in identifying positive feedback about coffee products. However, it misclassified 270 neutral instances as positive and 505 negative comments as positive, indicating difficulty in differentiating neutral and negative from positive sentiments in customer feedback.

Table 6
A comparative evaluation of LSAnArTe with Amazon Comprehend performance metrics.

APPROACHES	CLASS	R	P	F1	ACC
LSAnArTe	+1	96.62	98.08	98.22	**93.79 %**
	−1	89.91	98.87	94.21	
	0	82.96	53.30	64.71	
Amazon Comprehend	+1	53.41	78.19	63.47	**51.09 %**
	−1	50.03	77.98	60.95	
	0	52.46	12.62	20.35	

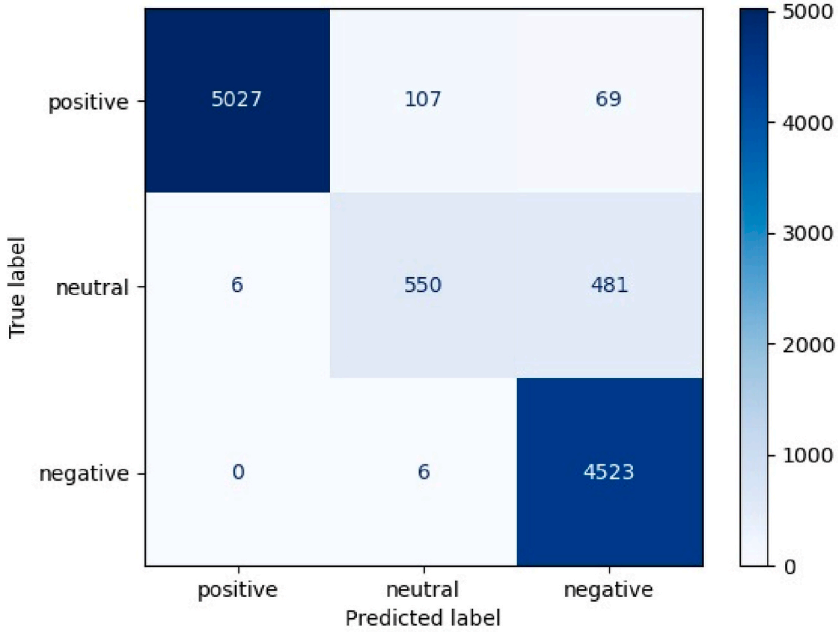

Fig. 8. LSAnArTe confusion matrix - Arabic sentiment analysis on coffee products.

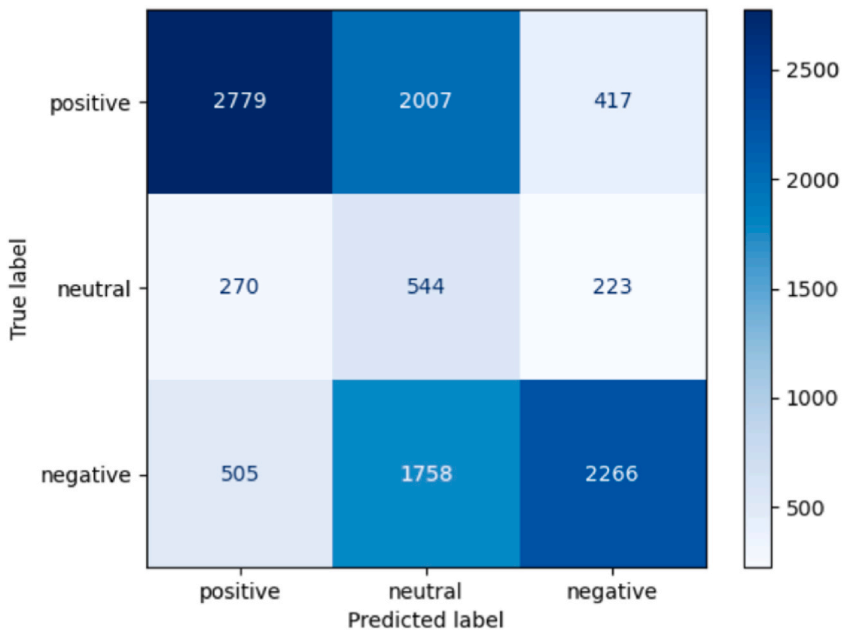

Fig. 9. Amazon comprehend confusion matrix - Arabic sentiment analysis on coffee products.

The Amazon Comprehend correctly identified 554 neutral sentiments and misclassified 2007 positive comments as neutral and 1758 negative comments as neutral, revealing a challenge in accurately categorizing sentiments. Notably, the lack of proper neutral sentiment predictions suggests a potential gap in the model's capacity to detect neutral feedback. However, Amazon Comprehend demonstrates good capacity in capturing negative comments by correctly classifying 2266 negative comments.

The colour gradient used in the matrix highlights the distribution of predictions, with the intensity of the colors corresponding to the frequency of instances, illustrating the model's performance visually. This analysis indicates that while Amazon Comprehend is effective in identifying negative and positive sentiments about coffee products in Arabic on social media, it needs refinement in accurately distinguishing between sentiment classes, especially in avoiding misclassifications and improving neutral sentiment detection.

6. Conclusion and future work

This paper delved into SA of Arabic textual feedback on social media concerning coffee products and aimed to precisely capture customer perceptions. We introduced the innovative LSAnArTe (Lexicon-based Sentiment Analysis on Arabic Texts) Framework, enhancing the understanding of customer sentiments in Arabic. This initiative sought to create a comprehensive Arabic sentiment lexicon, incorporating the AraSenti Arabic Lexicon database and utilizing Qalasadi for effective Arabic word lemmatization to address linguistic challenges. Our findings revealed that the LSAnArTe Framework achieved an impressive accuracy rate of 93.79 % in identifying customer sentiments towards coffee products from Arabic social media content.

The development of the LSAnArTe Framework represents a significant breakthrough in SA, enabling a deeper and more nuanced understanding of customer emotions from feedback in Arabic text. By customizing this tool to the specific lexicon of the coffee industry, we significantly enhanced the precision of sentiment interpretation. This advancement is especially relevant given the global and regional prominence of coffee, highlighting the importance of accurately assessing consumer sentiment. The LSAnArTe Framework not only pushes the boundaries of SA methodologies but also provides valuable market insights, assisting businesses in aligning their strategies with consumer preferences and trends more effectively. Through this research, we underscore the potential of lexicon-based Sentiment Analysis in Arabic, paving the way for more targeted and strategic business decisions in the coffee sector and beyond.

This work can be extended to include advanced detection methods using supervised, unsupervised and ensemble techniques. We may train classifiers to reliably recognize sentiment-bearing words in Arabic text by utilizing supervised learning methods like Support Vector Machines (SVM). Moreover, sentiment analysis results could be more resilient and reliable if ensemble learning techniques which combine multiple algorithms to improve prediction accuracy are used. These methods present promising directions for improving the LSAnArTe Framework's performance and improving its precision in accurately recording customer perceptions.

Ethics approval and consent to participate

Not applicable.

Consent for publication

We give the publisher the permission of the authors to publish the work.

Availability of data and materials

Data is available upon request.

Funding

N/A.

CRediT authorship contribution statement

Ohud Alsemaree: Writing – original draft, Validation, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Atm S. Alam:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Conceptualization. **Sukhpal Singh Gill:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Data curation, Conceptualization. **Steve Uhlig:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

N/A.

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