# Comparative analysis of machine and deep learning algorithms for semantic analysis in Iraqi dialect

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**ABSTRACT**

Text analytics, an essential component of artificial intelligence (AI) applications, plays a pivotal role in analyzing qualitative sentiments and responses in questionnaires, particularly for governmental and private organizations. Utilizing sentiment analysis enables a comprehensive understanding of people's opinions, especially when expressed in lengthy texts in their native language, with minimal constraints. This study aims to identify the determinants of electronic service adoption among Iraqi citizens. A set of 1,695 questionnaires were distributed to Iraqi citizens; obtained 1,234 responses that were increased via data augmentation to 1,393 comments. Four machine learning (ML) and three deep learning (DL) algorithms Naïve Bayes (NB), K-nearest neighbors (KNN), support vector machine (SVM), random forest (RF), as well as two variants of long-short-term memory (LSTM) networks and convolutional neural networks (CNN) were employed to classify qualitative feedback. Following rigorous training and testing, the NB classification algorithm exhibited the highest accuracy, achieving 82.89%.



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## 1. INTRODUCTION

Gathering and analyzing customer feedback is one of the most important parts of evaluating offered services, electronic (e-services) or traditional. This determines how happy customers are with the services they have received. This evaluation helps to identify the strengths and shortcomings of the service and enables for responsiveness to user needs. Especially after the coronavirus disease 2019 (COVID-19) pandemic, the use of e-services have increased remarkably [1]. Both quantitative and qualitative feedback systems have been widely used by service providers to assess their services. The former is numerical and includes percentages, rating scales, and scores, whereas the latter includes remarks and other formats [2]. In fact, methods relying on quantitative feedback are frequently linked with closed-ended questionnaires that may provide an immediate reaction to users' needs [3].

In this context, this paper proposes a method for opinion mining of customer feedback for e-services in Iraq. This study investigated sentiment analysis of customer feedback for e-services in Iraq. To the best of the researchers' knowledge, this is the first work dealing with such cases. While earlier studies dealt with general sentiment analysis of the Iraqi dialect from comments collected from social media such as Facebook or Twitter. For example in [4], the authors introduced a focus on sentiment analysis of Iraqi Arabic dialect from Facebook platform and experimented machine learning (ML) algorithms including Naive Bayes (NB), support vector machine (SVM), random forest (RF), and K-nearest neighbor (KNN). Also, Bahaaulddin *et al.* [5] proposed an Iraqi hate speech classifier for data collected from Twitter, which was evaluated against several ML algorithms. For methods experimenting deep learning (DL) models, the work in [6] also dealt with data collected from social media platforms specifically Facebook and experimented a word embedding model by training the ensemble using Doc2Vec representations. The purpose of this study is to analyze responses to an open-ended survey using ML and DL algorithms for Iraqi. Thus, this research can lay the foundation for future studies by other authors. To evaluate the factors influencing Iraqi individuals' adoption of electronic services, online questionnaires were administered to over a thousand Iraqis. A total of 1,234 user comments were collected via this method, then the size was increased to 1,393 comments for the purpose of data balancing. Since the corpus size is moderate, ML algorithms outperformed DL algorithms, achieving 82.89% accuracy with NB algorithm. The main contributions of this work are: i) creating an opinion mining dataset for Iraqi which will be publicly available after publication; ii) proposing and implementing an opinion mining model, and iii) evaluating the proposed model on different ML and DL algorithms, achieving an accuracy of 82.89%.

The remainder of this paper is structured as follows: section 2 provides background information about the opinion mining task. Section 3 discusses the related work. Section 4 outlines the proposed methodology, and section 5 concludes with avenues for future research.

## 2. BACKGROUND

Opinion mining, also referred to as sentiment analysis, is a fundamental task in natural language processing (NLP) aimed at discerning an individual's emotional state. The polarity of a text is determined by the beliefs or emotions underlying it, much like those defined by humans [7]. Understanding a customer's level of satisfaction with a product or service, as well as their political or religious viewpoints on a given issue, is pivotal for decision-making [8]. Notably, while 20% of the world's data is structured text, a staggering 80% is unstructured text, representing the majority of global data [9]. The rise of social media platforms and the necessity to express opinions on various subjects have propelled the demand for text analysis. However, predicting and recognizing patterns in unstructured text, which lacks a specific framework, has become challenging [10]. Users are encouraged to voice their opinions and sentiments through open questionnaire mechanisms to enhance electronic services for citizens. A usof an individual's emotions often requires open expression. Arabs, particularly in Iraq, prefer to articulate their viewpoints in their native dialect rather than in modern standard Arabic (MSA), often utilizing social networking platforms and questionnaires for this purpose [11].

The Iraqi dialect stands as one of the most widely spoken Arabic dialects, with nearly 40 million speakers in Iraq and neighboring Arab Gulf countries. Enriched by vocabulary from other languages like Kurdish, Persian, Turkish, and English, the Iraqi dialect reflects the cultural amalgamation that has shaped its linguistic landscape over centuries. This evolution draws from Sumerian, Akkadian, Babylonian, Assyrian, Aramaic, and Arabic linguistic influences throughout Iraq's history. The proliferation of written Iraqi dialect data in Iraq has seen exponential growth, largely sourced from social media applications, where Iraqis frequently express their opinions and sentiments [12].

In this study, the richness of the Iraqi dialect was leveraged, within the context of text analytics, employing both ML and DL methodologies to analyze consumer feedback on electronic services. ML algorithms, such as NB, KNN, SVM, and RF, along with DL architectures including long-short-term memory (LSTM) networks and convolutional neural networks (CNN), play a pivotal role in deciphering sentiments and discerning patterns within the vast corpus of Iraqi dialect data. By harnessing the diverse linguistic influences present in the Iraqi dialect, which incorporates elements from Kurdish, Persian, Turkish, and English, the proposed method acknowledges the cultural intricacies that shape Iraqi society. This interdisciplinary fusion of linguistic analysis and advanced artificial intelligence (AI) techniques allows for deeper insights into the factors driving the adoption of electronic services among Iraqi consumers.

## 3. RELATED WORK

Various approaches to sentiment analysis in Arabic depend on factors like the data source, application, and usability [12]. These approaches typically fall into unsupervised learning using dictionaries and supervised learning with classifiers, wherein ML algorithms train on datasets to construct classifiers for text prediction, often requiring manual labeling [13]. While sentiment analysis in English texts is well-documented, the analysis of classical Arabic and different Arabic dialects still lags behind [14].

Studies have shown promising results when applying supervised ML algorithms to analyze Arabic sentiments. For instance, in a study analyzing tweets in the Jordanian dialect and MSA, the SVM algorithm outperformed the NB classifier with an accuracy of 88.72% and an F-score of 88.27% [15]. Conversely, in another study focusing on Facebook comments in MSA or the Moroccan dialect, the NB algorithm yielded superior results compared to SVM [16]. Similarly, in a study on Tunisian dialect sentiment analysis, ML algorithms applied to a Tunisian training corpus achieved the highest accuracy [17].

However, research on sentiment analysis in the Iraqi dialect remains limited. Alnawas and Arici [6] proposed a sentiment analysis model using Facebook comments, finding SVM classifiers to be most effective achieving an F-score of 78%. Almosawi and Mahmood [18] developed an Arabic sentiment glossary, primarily from the Iraqi dialect, using a lexicon-based method with SVM yielding the best results. Zaki *et al.* [19] introduced a distributed method for real-time sentiment analysis of the Iraqi dialect on Twitter, enhancing performance using ML algorithms like DT and K-means; no results were reported in this work. Askar and Nur [20] introduced an annotated document for Mesopotamian and Iraqi dialects, providing polarity and emotion classifications for social networking site analysis. The authors managed to achieve an F-score of 65%. Moreover, it is worth noting that the annotated document for sentiment analysis in the Mesopotamian and Iraqi dialects, as introduced by Askar and Nur [20], was meticulously curated by experts proficient in Iraqi linguistics and cultural nuances. This careful annotation process ensured the accuracy and relevance of polarity and emotion classifications for analyzing social networking site data in the Iraqi context.

## 4. METHOD

This section describes the proposed method for opinion analysis in the Iraqi dialect, which comprises three main steps, namely; (A) data gathering and data annotation, (B) data augmentation, and (C) model creation as shown in Figure 1.

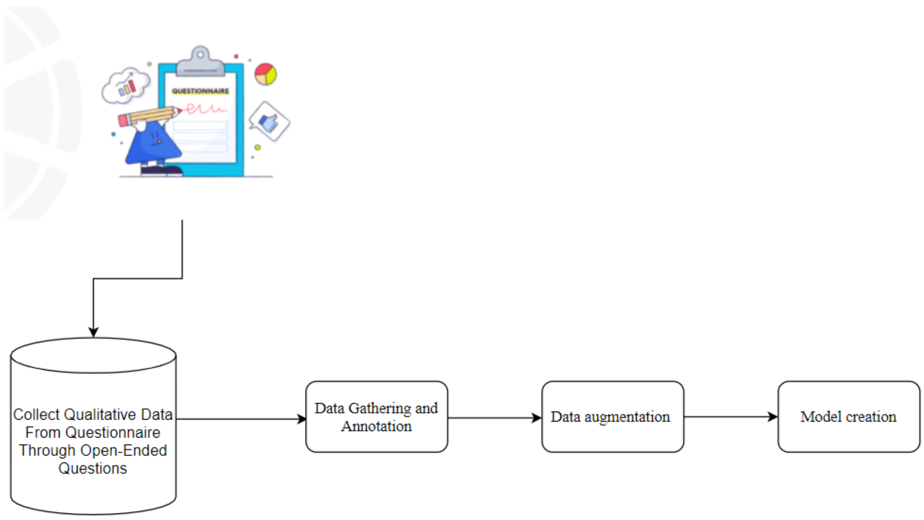


Figure 1. Sentiment analysis methodology

### 4.1. Data gathering and annotation

Data collection is a crucial component of any research project, and each type of data necessitates specific collection techniques. To address the shortage of resources for the Iraqi dialect, an electronic questionnaire was distributed to 1,695 Iraqi citizens and 1,234 comments were successfully collected. Consequently, the Iraqi corpus dialect (IQCD) is introduced, which includes feedback from Iraqi citizens about e-services in Iraq. The questionnaire was specifically designed to explore factors influencing the adoption of electronic services in Iraq from the perspectives of the service users.

After data preprocessing, a collection of 1,234 comments was obtained, which was annotated by two experts of the Iraqi dialect. Experts in this dialect were asked to label the data according to the estimated opinion as positive, negative, or neutral. The Cohen Kappa index for the annotators agreement was 0.684. Following this step, the distribution of labels in the IQCD dataset is as follows: 469 Positive, 491 negative, and 274 neutral (some examples are presented in Table 1). The dataset is unbalanced, showing significant disparities in the number of cases or samples per class. To mitigate this, the most effective strategies include resampling and data augmentation. Thus, a step of data augmentation was essential to address this issue.

Table 1. A sample of qualitative comments from Iraqi citizens' comments about e-government services in Iraq

| Label | Examples in Arabic | Their translation |
|---|---|---|
| Positive | سهلة الاستخدام ، واختصار للوكت<br>ماكو بيها الروتين المزعج<br>تقليل الكلف ، ظاهرة جدا حضارية<br>ارتقاء بالمستوى العام | Easy to use, saves time, bypasses annoying routine, reduces costs, is a very civilized phenomenon, and raises the general level. |
| | كلش مفيدة وزينة ومرتبة وبيها هواي<br>امور ايجابية لانها تلخصك من التعب وماكو<br>بيها رشاوي والحكومة العراقية دا تشتغل<br>خوش شغل في هذا الموضوع | It is useful, good, and tidy, and it has positive things in it because it saves you from fatigue, and there are no bribes, and the Iraqi government is doing a good job on this issue. |
| Negative | كلش زفت ومشاكلها ما تخلص خصوصا<br>موضوع السيرفرات مالتهم و الامان من<br>ناحية ثانية مقارنة بالدول الاقليمية | Everything is bad and its problems are not going away, especially the issue of servers and security on the other hand compared to regional countries. |
| | ماكو شي اكدر اسوي عن طريق الانترنت<br>في العراق ماكو نظام حجز مواعيد، ماكو نظام<br>يشمل معلوماتي يكدر يساعدني اطلع وثيقه<br>او اي شي يخصني | There is nothing I can do via the Internet in Iraq. There is no system for booking appointments. There is no system that includes my information that can help me see a document or anything that concerns me. |
| Neutral | عدنه الخبرات العلمية القادره تحول كلشي .<br>الكتروني لكن المواطن العراقي لحد الان | We have scientific expertise capable of transforming everything electronic. But until now, the Iraqi citizen who wants to apply for something electronic goes to the owner of an office to help him with this application. |
| | من يريد يقدم على شي الكتروني<br>يروح لصاحب مكتب يساعده بهذا التقديم<br>قليل مايتوفر عدنه هذا الشي مع العلم انو<br>احنه نحتاجه وراح يقلل من هوسه الاوراق<br>والمعاملات والتاخر بالوقت وكذلك الرسوم | This is something we rarely have, even though we need it, and it will alleviate our obsession with papers, transactions, time delays, and fees. |

### 4.2. Data augmentation

Data augmentation is a widely used technique in ML and DL to increase the quantity and diversity of a training dataset [21]. In the context of NLP, data augmentation strategies can include phrase rearranging, paraphrasing, random word insertion or deletion, and synonym substitution [22]. To address the imbalance in the IQCD dataset, particularly the under representation of neutral sentences, data augmentation is employed. Originally, the dataset contained only 274 neutral sentences compared to a higher count of other sentiment tags. To balance this, the number of neutral sentences was increased to 449 by substituting some words in the Iraqi dialect with their synonyms. The augmented dataset comprises 1,393 sentences, with 1,128 unique phrases. The updated distribution of sentences in the IQCD dataset is 457 positive, 487 negative, and 449 neutral. Table 2 provides a comparison of the dataset statistics before and after data augmentation.

Table 2. Statistics of the dataset obtained

| Description | # Sentences | # Unique sentences | # Words | # Unique words |
|---|---|---|---|---|
| Before data augmentation | 1,234 | 1,101 | 10,282 | 3,390 |
| After data augmentation | 1,393 | 1,128 | 11,526 | 3,364 |

### 4.3. Model creation

In this study, various ML and DL algorithms were explored for implementing a sentiment analysis model using the IQCD corpus. Following the data separation in the literature review, different sets were tested (70:30, 80:20). Both ML and DL algorithms were tested using Python programming language and adequate libraries dedicated for this purpose. The tested algorithms are RF, NB, SVM, KNN, and LSTM, Doc2Vec-LSTM, and CNN. The best results achieved were with the NB algorithm using the second configuration (80:20), achieving an accuracy of 82.89%. Figure 2 illustrates the performance values, accuracy-wise, obtained for all algorithms tested with the IQCD dataset.

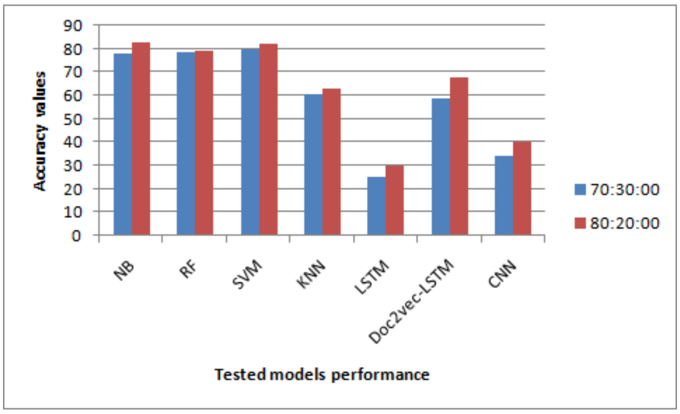


Figure 2. Performance of tested algorithms

## 5. EXPERIMENTS AND RESULTS

Four popular ML algorithms' performance was evaluated: RF [23], KNN [24], NB [25], and SVM. Also, three DL algorithms were tested, namely: LSTM, a Doc2vec and LSTM model, and CNN. The employed parameters are detailed in Table 3. As shown in Table 3, different algorithms employing various parameters were evaluated. Indeed, many experiments were performed in order to obtain good results. The results for the assessed ML algorithms are summarized in Table 4 and visually presented in Figure 3. The KNN algorithm exhibits competitive precision but lags behind other algorithms in terms of recall, resulting in lower overall effectiveness (see Table 4). This highlights the importance of considering multiple performance metrics when evaluating ML algorithms for sentiment analysis tasks.

Since DL algorithms have shown superiority in sentiment analysis and opinion mining, experiments with some DL algorithms were conducted in addition to ML algorithms. The proposed method in this study tended to have an inordinately higher performance when using ML algorithms rather than DL algorithms due to the moderate size of the dataset.

Experiments with the LSTM algorithm initially yielded discouraging results, achieving only 30% accuracy with the first configuration. After adding some layers, specifically an embedding layer for the Doc2Vec model, the accuracy improved to 68%. Figure 4 provides an overview of the different architectures employed in the experiments. Additionally, the CNN algorithm was experimented with, but better results were not achieved, obtaining an accuracy of 40.16%. Figure 5 presents the architecture of the employed CNN model.

Table 3. Configuration of the tested algorithms

| Model | Parameters |
|---|---|
| RF | n_estimators=100, random_state=42 |
| KNN | n_neighbors=3 |
| NB | default configuration in the library MultinomialNB() of sklearn |
| SVM | C=1.0, kernel='linear', degree=3, gamma='auto' |
| LSTM | padsequence = 200, dense=16, batch_size=32, epochs=15, activation='sigmoid', optimizer='adam', loss='binary_crossentropy' |
| Doc2vecLSTM | dm=1, vector_size=20, window=8, min_count=1, workers=1, alpha=0.065, batch_size=32, epochs=30, activation='softmax', optimizer='adam', loss='binary_crossentropy' |
| CNN | padsequence=200, batch_size=128, epochs=6, activation='relu', optimizer='adam', loss='binary_crossentropy' |

Table 4. Obtained results with ML algorithms (RF, KNN, NB, and SVM)

| ML algorithms | Precision | Recall | F1-score | Accuracy |
|---|---|---|---|---|
| RF | 79.45 | 79.19 | 79.14 | 79.19 |
| KNN | 78.50 | 62.92 | 60.82 | 62.92 |
| NB | 82.89 | 82.54 | 82.46 | 82.54 |
| SVM | 82.16 | 82.06 | 82.07 | 82.06 |

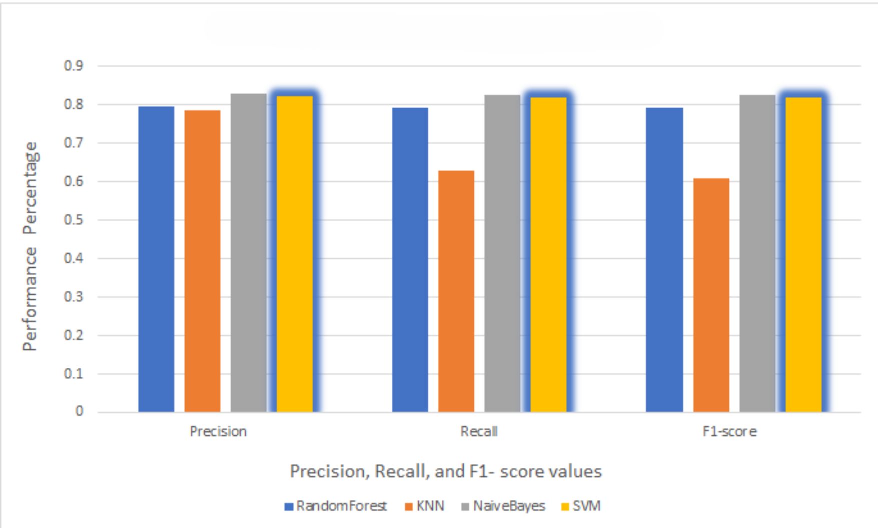


Figure 3. Results for ML algorithms (precision - recall - F-score)

Table 5 provides a comparative summary between ML and DL algorithms, highlighting the best results achieved in the various experiments. Indeed, as shown in Table 5, the DL algorithms, specifically LSTM and CNN, did not achieve good results, with accuracy values of of 30% and 40.16% respectively. This study suggests that to enhance the tested models, specifically LSTM is not associated with poor performance in DL algorithm results rather in the size of the dataset. To improve the obtained results, the proposed model may benefit from some layers that were added, including an embedding layer implementing Doc2Vec, which increased the accuracy to 68%. However, it still falls short in comparison to ML algorithms. without adversely impacting other results. Notably, the NB algorithm achieved the best performance with an accuracy of 82.54%.

To assess the effectiveness of the proposed method, a comparison with previous methods was realised. The work of [6] experimented the SVM model that was employed in this work. Their best achieved result was an F-score of 78%, whereas the best achieved F-score in this work was 82.46% with the NB algorithm and with SVM the F-score achieved was 82.07% still better than the results in [6]. Overall, this study found that, compared to state-of-the-art methods, the proposed method obtained promising results that correlate with result improvement by enlarging the corpus size.

The potential of this work is that it deals with real-life expression, i.e., feedback collected from customers of e-services rather than general sentiment expression collected from social media as it is the case for most state-of-the-art methods . However, further and in-depth studies may be needed to confirm the importance of sentiment analysis in Arabic, especially regarding the local dialects of this language, with further work on the corpus increasing its size and generalizability.

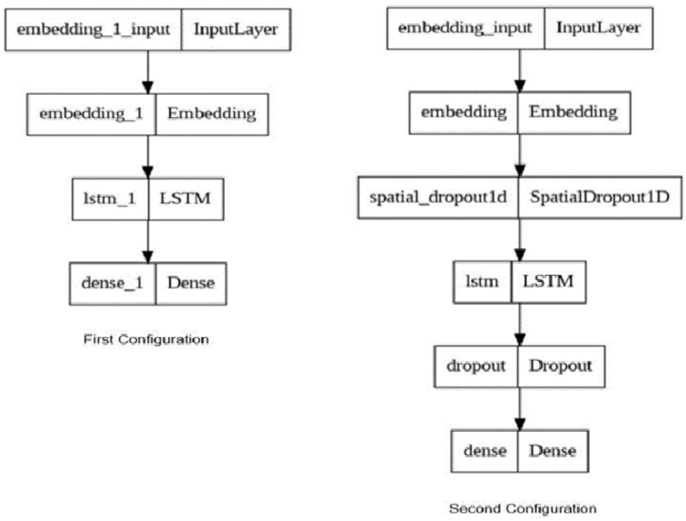


Figure 4. LSTM model architectures

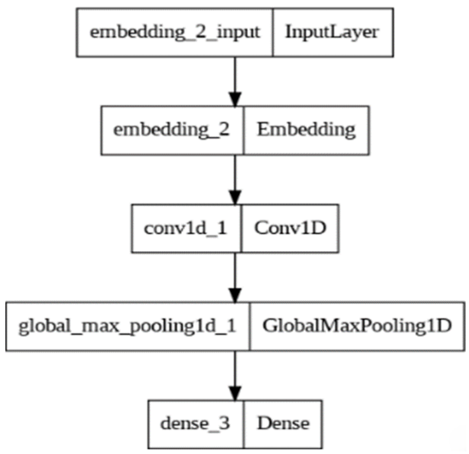


Figure 5. CNN model architecture

Table 5. Comparison of ML and DL algorithms

| Algorithms name | Accuracy (%) |
|---|---|
| ML algorithms | |
| RF | 79.19 |
| KNN | 62.92 |
| NB | 82.54 |
| SVM | 82.06 |
| DL algorithms | |
| LSTM | 30 |
| LSTM with Doc2Vec | 68 |
| CNN | 40.16 |

## 6. CONCLUSION AND FUTURE WORK

In this paper, a method for opinion mining for the Iraqi dialect was presented, specifically the feedback for electronic services gathered from Iraqi users. The proposed method investigated collected reviews from distributed questionnaires to over a thousand Iraqi citizens, which were then cleaned and annotated to create the IQCD dataset. Due to a clear imbalance in the corpus, data augmentation was employed to balance the labels and thus augment the size to 1,393 from an initial size of 1,234.

After training a spectrum of ML and DL models, the best achieved accuracy was 82.89% utilizing the NB algorithm. Given the modest size of the IQCD dataset, the performance of DL models fell short, with the doc2vec-LSTM model yielding the highest accuracy score of 68%. The recent observations suggest that the accuracy of the obtained results provides conclusive evidence that this phenomenon is related to the change in the quality of data collected from social media, its processing, cleaning, annotation, and removal of useless information from it.

Future studies may explore pioneering novel approaches in this domain and advancing research on the Iraqi Arabic dialect. With feasible ways of producing the IQCD dataset both in breadth and size is to be considered through direct data acquisition efforts or by leveraging data augmentation techniques. Furthermore, exploring the realm of transfer learning is also intended, particularly with pre-trained Arabic models such as AraBERT, AraElectra, and CamelBERT, aiming to enhance the efficacy of the achieved results.

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