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Arabic Sentiment Analysis Evaluation of Saudi Arabia's Telecommunication Using Several Deep Learning Algorithms

Journal of Electrical Systems

Abstract: - Sentiment analysis (SA) is a technique that applies natural language processing (NLP) in order to analyze and classify the emotion in sentiment reviews. SA is responsible for analyzing people's feelings, opinions, and experiences that are shared through the Internet and social networks. In this paper, we focus on investigating, evaluating, and improving Arabic sentiment analysis (ASA) models, datasets, and challenges. ASA has several difficulties, like language's morphological features, many dialects, no clear and uniform corpora, low accuracy, and restricted ASA material. In order to do that, we do a full analysis and evaluation of Arabic sentiment analysis models and datasets that target e-marketing services such as telecommunication, health, and books. We evaluate our data set, called Sara, with several Arabic sentiment datasets in terms of brief description, dataset size, source of collecting data, field type, and abbreviation. We enhanced our previous models by using ensemble learning average techniques. The accuracy of our enhanced model has increased and now reaches around 97%. Also, we evaluate our developed ASA using deep learning (DL) algorithms with other ASA models in the field of e-marketing. Our models have significant improvements in terms of performance compared with other works, where our three models, CNN-Model, LSTM-Mode2, and CNN+LSTM-Model3, have accuracy of 96.83%, 94.74%, and 96.91%, respectively.

Keywords: Arabic sentiment analysis, Deep learning, Sara-Dataset, Performance, LSTM, CNN, Ensemble learning, Telecommunication

I. INTRODUCTION

Sentiment analysis (SA) is a very important model for analyzing social media content. SA is considered an intelligence mechanism to analyze people's opinions, whether they are positive or negative. ASA is used to analyze and classify Arabic people's emotions toward e-marketing products on social networking. Customer opinions in various areas, such as e-marketing, business, and other fields, are determined using SA. ASA has several problems, such as the lack of available datasets and the language's morphological features [1–4].

Figure 1. Arabic Sentiment Models, And Datasets Evaluation.

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Machine learning (ML) consists of artificial neurons that serve as the main computing units and networks. These neurons are utilized to represent their interconnectedness. DL is an enhancement model from machine learning in terms of performance (e.g., accuracy, precision). Deep learning has several techniques, such as CNN and LSTM [5].

As depicted in Figure, we target four parts to develop and evaluate an Arabic sentiment analysis model using DL models. First, we develop an ASA dataset called Sara-dataset. Second, we compare our dataset to others ASA datasets. Third, we develop three ASA models that classify Saudi Arabians toward communication companies. Fourth, we compare our sentiment analysis models with other models .
The reset of paper is organized as follows: Section 1 describes an introduction to sentiment analysis and Arabic sentiment datasets. Background on Arabic sentence analysis and deep learning are discussed in Section 2. In Section 3, we explain Saudi Arabia's telecommunications dataset and do a comparative evaluation with other Arabic sentiment datasets. The evaluation of our developed Arabic Sentiment Analysis models and a comparative evaluation with other ASA models are described in Section 4. Finally, we introduce our conclusion and future works in Section 5.

II. BACKGROUND

2.1 ARABIC SENTIMENTS ANALYSIS

Artificial intelligence is considered as one of the computer science disciplines, AI is the computer systems' mimicking human functionality. There are many applications of AI such as speech recognition, NLP [6]. Sentiment analysis uses NLP to categorize and evaluate Arabic speakers' feelings toward e-marketing items on social media [7]. Through social media and the Internet, people are sharing their knowledge and revealing their thoughts and feelings. This typically results in huge data communications via the Internet. However, the majority of this data may be usefully examined; for instance, the majority of businesses and political campaigns rely on communication sites to gather public opinion and determine if it is neutral, favorable, or unfavorable [8, 9].

It was Nasukawa, who initially proposed the notion of SA. SA began with natural language processing (NLP), which examines emotions, human responses, viewpoints, and information from social networks as well as website content. SA makes it easier to categorize concepts and viewpoints as neutral, negative, or positive [8]. SA is a textual analysis that is often utilized on websites and in social media. SA responds to consumer inquiries and reviews of any product, which boosts the business's revenues. Arabic sentiment analysis for E-marketing in social media (e.g. tweeter) is still weak and needs more effort. In addition, creating standard Arabic Tweets or an Arabic e-marketing product dataset is not an easy task [9, 10].

An artificial intelligence technique called Arabic Sentiment Analysis (ASA) is used to examine people's opinions, sentiments, and reactions to various goods and services on social media and business websites. Using DL to create sentiment analysis models to enhance e-marketing strategies. A few studies use deep learning algorithms to target ASA in e-marketing. Arabic presents a lot of challenges, including a lack of Arabic corpora and datasets, as well as worse performance when creating and developing ASA models. The ASA methodology, like SA, involves five steps for data processing [11], as shown in Figure 2.

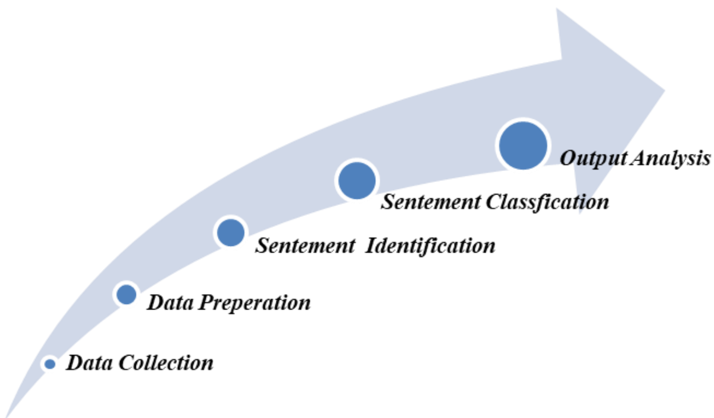

Figure 2. Sentiment Analysis Steps [11].

2.2 DEEP LEARNING

ML is a subset of artificial neural networks, whereas DL is regarded as machine learning. as shown in Figure 3. It is known that DL is a technique used to improve performance, accuracy, and running time. The fundamental computational unit is the artificial neuron, and networks are used to characterize how interconnected they are [5]. Deep learning has six compounds.

A neuron receives input from predecessor neurons. Connections and weights are key components connecting the input and output neurons. A weight is subsequently assigned to each link. Propagation function: It serves as an input for the output that is produced. Learning rule: It is employed to alter the neural network's parameters. GPU (Graphics Processing Unit) and PSU (Power Supply Unit).

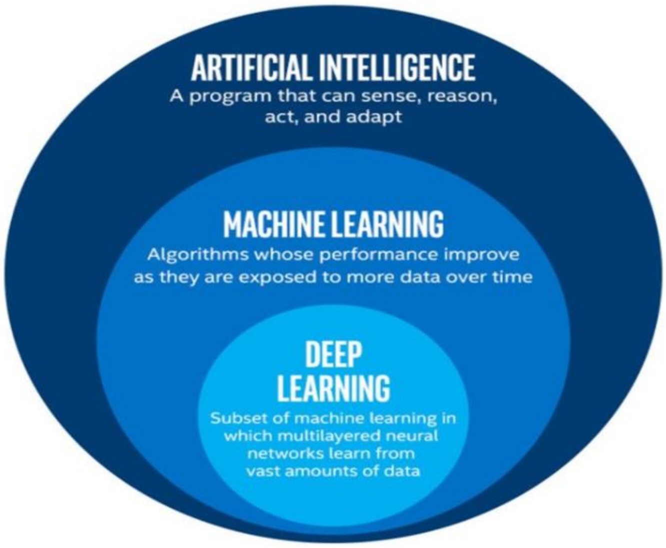

Figure 3. Deep Learning [12].

2.2.1 CONVOLUTIONAL NEURAL NETWORK (CNN)

CNN is considered a deep learning network with a multilayer network. Each of the several hidden layers of CNN is made up of several two-dimensional planes that are densely packed with neurons [13]. Figure 4 depicts a CNN structure.

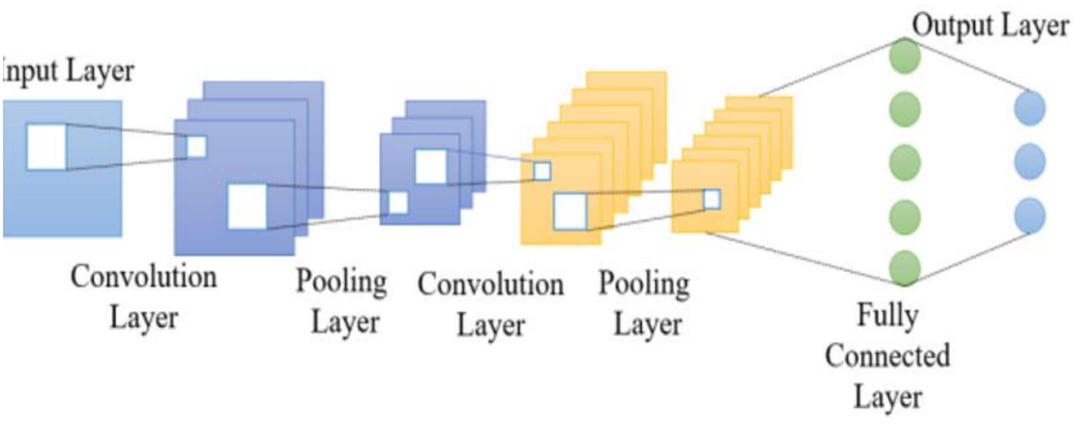

Figure 4. Typical CNN Architecture [13].

CNN is created by laying many construction components together, where these layers are input, convolutional, pooling, fully connected, and output. When a loss function is used to calculate the performance under specific weights over more than one fully connected layer, Forward propagation is the process by which input data is converted into output across these levels [14].

2.2.2 LONG SHORT-TERM MEMORY (LSTM)

LSTM was created to get around the standard RNN's shortcomings with regard to creating long-term dependencies. As seen in Figure 5, the LSTM unit is composed of the gate, memory cell, output, and input gate. The memory cell is in charge of holding values throughout time, while the additional gates control how data be entered and exits the cell. Figure 5 reports that LSTM has two structures. First, an LSTM with a stored-value cell and a couple of gates is displayed in Figure 5.a. Conversely, Figure 5b shows an LSTM equipped with a forget gate and a memory cell. In addition, an LSTM cell consists of a single input layer, a single output layer, and one self-connected hidden layer. The hidden unit could have building blocks that can be fed into LSTM cells one after the other [15].

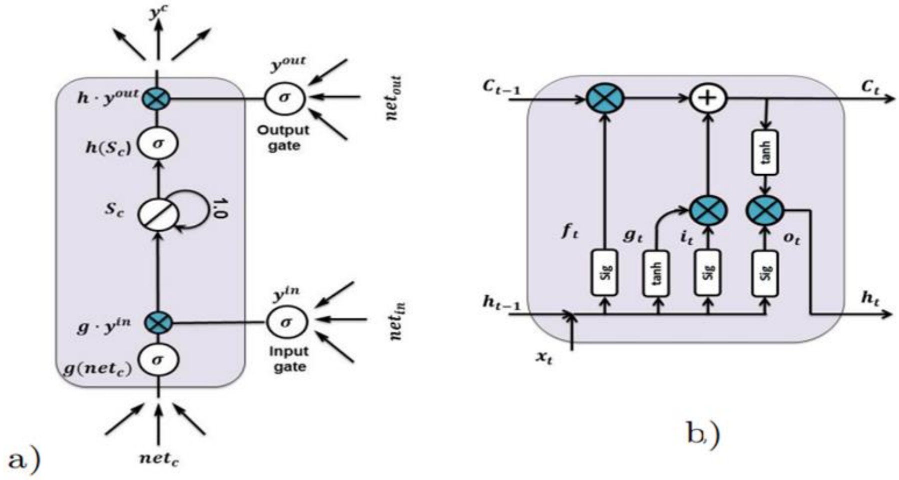

Figure 5. LSTM Structure [15].

2.2.3 COMPARISON BETWEEN TRADITIONAL MACHINE LEARNING AND DEEP LEARNING

Table 1 compares DL with Ml in terms of definition, concept, connection, application areas, compounds, architecture examples, accuracy, time, hyper-parameter tuning, and hardware dependency. It is clear that traditional machine learning uses networks or connections to transfer data. DL applied alteration and extraction of characteristics aimed at establishing a connection between inputs and related brain neural responses. Traditional machine learning is considered to have full connections between layers, but in deep learning, they are only partially. Deep learning accuracy is better than machine learning.

Table 1. ML Vs. DL.

Comparison keys	ML	DL
Means	Is artificial intelligent mechanism where each artificial neuron as computing unit uses as networks connection	It is a ML. DL extracts features using non-linear computation
Data transfer	Using Networks	Used transformation and feature extraction
Connection	Fully connects between layers	Partially connect between layers
Compounds	Neurons, connections, Propagation function and Learning rule	Such as ML together with GPU and PSU
Algorithm example	Recurrent networks	CNN and LSTM
performance	Less than DL	More than ML
Time	Take more time in training	Take more time in training
Hyper-parameter	Few	Several
Hardware dependency for training	Depend on CPU	Depend on CPU and GPU

III. SENTIMENT ANALYSIS DATASETS EVALUATION

3.1 SAUDI ARABIA'S TELECOMMUNICATION DATASET

Sara et al. [15, 22] created a new Arabic dataset that was collected from Twitter. By gathering consumer feedback, they aim to enhance the number and quality of services provided by three Saudi Arabian communication companies. The classes of the Sara dataset are positive and negative. The targeting companies are STC, Mobily, and Zain. Many preprocessing algorithms are used, such as removing URLs, removing Arabic stop words, and other techniques. The number of dataset tweets after preprocessing techniques is 27294. There are thirteen features in the dataset. Figure 6 shows the number of classes in each company. Please see the papers [15, 22] for further information.

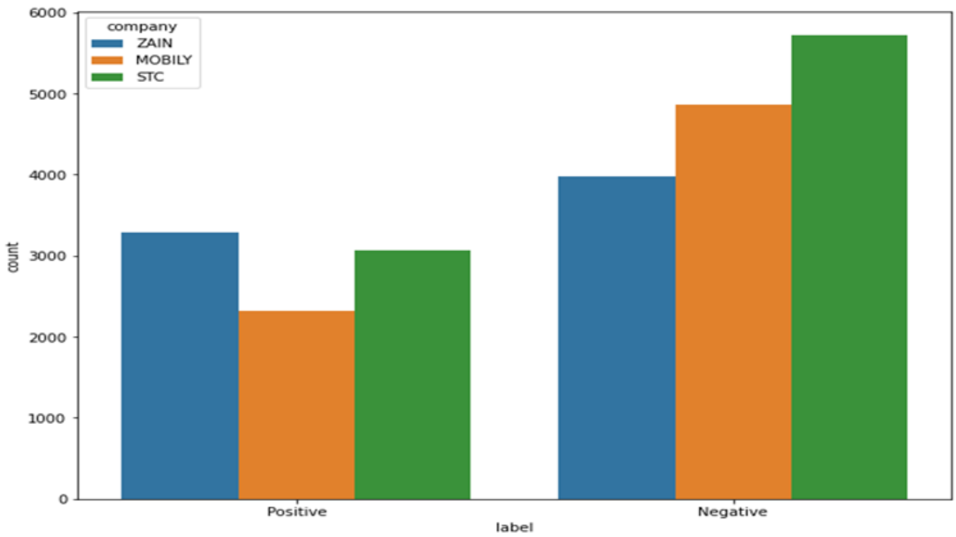

Figure 6. Classes distribution of dataset [22].

3.2 COMPARATIVE EVALUATION OF SENTIMENT ANALYSIS DATASETS

Twitter offers a crucial forum for thought and communication. Users can talk about a variety of events, goods, and e-marketing tactics. Numerous studies have examined consumers' perceptions of items as well as public opinions and attitudes toward particular services [16, 17, 18, 19]. In this subsection, we will explain the most famous datasets and our own dataset, called Sara-dataset.

1. OCA (Opinion Corpus for Arabic): This Arabic corpus includes 0.5K good and bad movie posts. OCA collected Arabic pages and blogs. But the main drawback is the limited size and limited film domain.
2. It is an Arabic cuprous consisting of 63K book reviews. These reviews are rated according to five stars. OCA is a limited domain, which is books filed.
3. NA is an Arabic sentiment dataset with a size of 33K for multiple domains (e.g., accommodation.
4. Arabic Health Services Dataset (AHSD): it contains more than 2000 tweets. AHSD considered the dataset unbalanced. The domain of AHSD is medical services, especially medical care.
5. Arabic Twitter (ArTwitter). It contains political statistics gathered from social media on Twitter. There are hundreds of tweets. It is considered a balanced dataset.
6. Arabic Sentiment Tweets Dataset (ASTD). It contains 2479 Arabic tweets. ASTD is not a balanced dataset where positive and negative posts are not equal.
7. Human−Annotated Arabic Dataset (HAAD).
8. Ar-Twitter ASDT (Arabic Sentiment Tweets Dataset),
9. Stanford Sentiment Tree Bank (SSTB)
10. Stanford large movie review (SLMR)
11. Amazon review dataset
12. Main-AHS,
13. Sub-AHS
14. Tunisian Sentiment Analysis Corpus (TSAC). It is an Arabic-Tunisian dialect. They collected the comments of 17,000 Facebook users. These comments are related to Tunisian radio and television [21].

15. CMU-MOSI
16. MOUD
17. Our dataset which coin Sara-Dataset [15, 22].

Table 3 shows the evaluation of the most Arabic sentiment datasets in terms of name, size, brief description, the data collection source such twitter and Facebook, the type of data or field such political, economic, health and telecommunication. Sara-dataset is considered a very large dataset compared with others dataset. It is also targeting. In addition, we do most of preprocessing algorithms such as Embedding, Filtering, normalization, stop-word removal, negation, stemming, tokenization, and segmentation of tweets.

Table 3. Evaluation of Arabic Sentiment Datasets.

Arabic Dataset Name	Size	Description	Source	Field	Abbreviation
LABR [23]	63K	First Arabic Book Review corpus, negative rating represents 1 and 2. Positive rating represent as 4 and 5. The neutral rating represent as 3.	Limited for Book review from twitter	Books	Large Scale Arabic Book Reviews
OCA [24]	limited size	Arabic Corpus includes 500 film reviews	Arabic pages and blogs	Films	Opinion Corpus for Arabic
ArTwitter	thousands of posts	Politics corpus collected from Twitter social media.	thousands of records	politics	Arabic Twitter Dataset
AHSD	2K posts	Not balanced dataset. 2K posts represent health services	Twitter	Medical services	Arabic Health Services Dataset
HSDC [20]		a collection of many datasets on hate speech in various languages, including Arabic.	Social media	bad speech in various languages,	Hate Speech Dataset Catalogue
Sara-Dataset [15, 22]	50532	A new dataset collected from twitter. It considered as new Arabic dataset for Saudi Arabian communication companies. The selected companies are (STC), Mobily, and Zain	Twitter	Telecommunication	Sara dataset for Saudi Arabic telecommunication company
ASTD [25]	10K	Public corpus collects manually from Tweets. Divided into objective, subjective positive, subjective, and negative.	tweets	Just for Egyptian dialect.	The Arabic Sentiment Tweets Dataset

MASC [26]	8K reviews	Public Arabic language corpus for several delicate and domains. Consist of 8,860 reviews. The reviews were collected manually from multiple sources (e.g., the Jeeran website). The dataset consists of fifteen domains.	website, and Google Play, Twitter, and Facebook.	Multi-domain (e.g., Jeeran website, and Faceboo k).	Multi-domain Arabic Sentiment Corpus

IV. SENTIMENT ANALYSIS MODELS EVALUATION

4.1 EVALUATION OF OUR DEVELOPED ARABIC SENTIMENT ANALYSIS MODELS

Results Obtained Using CNN And LSTM:

Sara et al. [15, 22] developed an ASA model using a deep learning algorithm (CNN) with a Sara dataset and several hyperparameters, as shown in the first row of Table 4. The best accuracy performance achieved when using an optimizer called Adam was 96.34% with a 64-batch size. The accuracy is 96.83% when using. Adam with a 32-batch

Table 4. Measurement Performance for CNN Model

Model	Epochs	Batch-size	Optimizer	Validation	Accuracy
Model1-CNN	10	32	Adadelta	62.98%	47.14%
			Adagrad	83.38%	86.63%
			Adam	95.48%	96.83%
		64	Adadelta	62.98%	47.14%
			Adagrad	68.63%	61.34%
			Adam	94.75%	96.34%
		128	Adadelta	62.98%	47.14%
			Adagrad	62.98%	47.14%
			Adam	62.98%	94.38%

Sara et al. [15, 22] developed an Arabic sentiment analysis model using a deep learning algorithm (LSTM) with Sara_Dataset. This paper uses several parameters, such as epoch. As depicted in Table 5, the best performance is achieved when LSTM is used with the Adam optimizer, where the accuracy is 94.97%.

Table 5. LSTM Model performance with several parameter.

Model	Epochs	Batch	Optimizer	Performance-Validation	Performance-Accuracy
model2-LSTM	10	32	Adadelta	62.98%	47.14%
			Adagrad	63.14%	47.14%
			Adam	95.03%	94.97%
		64	Adadelta	63.05%	47.14%
			Adagrad	62.98%	47.14%
			Adam	94.27%	93.47%
		128	Adadelta	62.94%	47.26%
			Adagrad	62.98%	47.14%
			Adam	93.22%	93.79%

In this paper, we enhance our model by applying the combination of two models (ensemble learning)—the CNN and LSTM models—to improve the model's accuracy. We use several hyper-parameters, such as the optimizer, as depicted in Table 6. The best performance in terms of accuracy (94.99%) is achieved when the Adam optimizer is used with a 32-batch size. And 96.91% with 64-batch size and 93.52% with 128-batch size, as shown in Table 6.

Table 6. Our ensemble learning model performance.

Model	Epochs	Batch-size	Optimization techniques	Validation accuracy	Accuracy
model2-LSTM	10	32	Adadelta	62.98%	47.14%
			Adagrad	79.84%	83.39%
			Adam	94.62%	94.99%
		64	Adadelta	62.98%	47.14%
			Adagrad	70.8%	62.05%
			Adam	96.36%	96.91%
		128	Adadelta	62.98%	47.14%
			Adagrad	62.98%	47.14%
			Adam	93.78%	93.52%

Table 7 shows that our three models' accuracy: CNN-Model1, LSTM-Model2, and CNN+LSTM Model3 is 96.83%, 94.97%, and 96.91%, respectively. Which indicates that ensemble learning achieves better accuracy than the other two models. merge LSTM with CNN models to improve the performances of models 1 (CNN) and 2 (LSTM). We deploy ensemble learning approaches, namely bagging techniques.

Table 7. Best results evaluation of our models in terms of several parameters.

Model name	Deep learning algorithm	Batch-size	Epochs	optimizer	Accuracy
CNN-Model1	CNN	32	10	Adam	96.83%
LSTM-Mode2	LSTM	32	10	Adam	94.97%
CNN+LSTM-Model3	CNN+LSTM	64	10	Adam	96.91%

4.2 DEVELOPED SENTIMENT ANALYSIS MODELS VS. OUR DEVELOPED MODELS

The main part of this paper is to evaluate our models against other ASA models. Several studies of Arabic sentiment analysis in e-marketing have been collected. As depicted in Table 8, the evaluation process depends on the model's name, deep learning techniques, dataset, e-marketing area, and accuracy.

Table 8. sentiment analysis models vs. our developed models.

Models name	Deep learning techniques	Data set	Area	accuracy
[27]	SVM	Collected From Twitter. contains 1103tweets	political	84.01%
[28]	LSTM+CNN	HTL and LABR	book rating	85.38%
[29]	Machine learning and deep learning	The dataset consists of 500 tweets.	Education Filed	Machine learning (DT, SVM) achieves

				85%. Deep learning (LSTM)achieves 90%
[30]	ASTD	Ensemble learning CNN+LSTM	Marketing	65.05%
[31]	Twitter Arabic Hotels reviews	STM and Bidirectional LSTM	Hotel rating	82.6%
[32]	SemEval dataset contains of 4K tweets	Bidirectional LSTM	Determining state of a person from their tweet	75.5%
Our model CNN-Model1	CNN	Sara-dataset	Saudi Arabia Telecommunications	96.83%
Our modelLSTM-Mode2	LSTM	Sara-dataset	Saudi Arabia Telecommunications	94.97%
Our model CNN+LSTM-Model3	CNN+LSTM	Sara-dataset	Saudi Arabia Telecommunications	96.91%

As seen in Table 8, our models outperform and have significantly higher performance than other models. Model 3 using a combination of CNN and LSTM achieves an accuracy of 96.91%, which is considered the best result compared with other models. In addition, we use accurate preprocessing techniques, such as Arabic embedding techniques.

V. CONCLUSION AND FUTURE WORKS

SA is an NLP technique used to classify customer opinions based on sentimental reviews. SA is responsible for analyzing people's feelings, opinions, and experiences that are shared through the Internet and social networks. In this paper, we focus on investigating, evaluating, and improving Arabic sentiment analysis (ASA) models, datasets, and challenges. ASA has several difficulties, such as the fact that there are no clear and uniform corpora. Also, ASA models have low performance in terms of accuracy. In order to do that, we did a full analysis and evaluation of Arabic sentiment analysis models and datasets targeting e-marketing services such as telecommunication, health, and books. We evaluated our data set, called Sara, with several Arabic sentiment datasets in terms of brief description, dataset size, source of collecting data, field type, and abbreviation. We enhanced our previous models by using ensemble learning average techniques. The accuracy of our enhanced model has increased and now reaches around 97%. Also, we evaluate our developed ASA models with other models that use machine learning and deep learning techniques. Our models have significant improvements in terms of performance compared with other works, where our three models, CNN-Model, LSTM-Mode2, and CNN+LSTM-Model3, have accuracy of 96.83%, 94.74%, and 96.91%, respectively.

Our future work is to use Transformer deep learning to enhance the accuracy of Arabic sentiment analysis in e-marketing, such as using BERT (Bidirectional Encoder Representations Transformer) [33], DistilBERT (Distillation BERT) [34], and GPT-3 (Generative Pre-trained Transformer) [35]. Also, we will employ our model to benchmark Arabic sentiment analysis.

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