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A combined Bi-LSTM-GPT Model for Arabic Sentiment Analysis

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Abstract: This research investigates the efficacy of ensemble learning within the field of Arabic sentiment analysis. Ensemble learning, which combines predictions from multiple models to enhance accuracy, has shown promising results when compared to individual models. Hence, we propose an ensemble learning model that integrates two robust models: a Bidirectional Long Short-Term Memory (BiLSTM) model and a Generative pre-trained transformers (GPT) model. The GPT model has previously demonstrated effectiveness in various Arabic natural language processing (ANLP) tasks. To examine the performance of our ensemble model, we separately trained the BiLSTM and transformer-based model using three different datasets. We combined the models by aggregating their final probabilities for each class. Through multiple experiments, we compared the effectiveness of the proposed ensemble model with the standalone models. The results clearly indicate that the ensemble learning models outperform the standalone models in Arabic sentiment analysis. Specifically, the proposed ensemble model that demonstrated an accuracy increase of nearly 7% when compared to the best standalone model.

Keywords*: BiLSTM, AraGPT, Arabic sentiment analysis, deep learning, ensemble learning*

1. Introduction

Nowadays, the internet has become one of the most rapidly changing and fast-growing technologies. With its wide reach and ease of access, the internet has become an integral part of our lives. According to recent statistics, the total number of internet users across the globe has been growing steadily at an average annual rate of over 5%. Globally, internet users communicate, share content and express their opinions or their sentiments on the internet on a wide range of topics in discussion groups, blogs, forums and other public websites. In the Arab region, internet users are highly interactive on social media platforms and blogging websites. These platforms have gained immense popularity due to their ability to connect people and enable them to share their thoughts and experiences. Social media platforms such as Facebook have played a critical role in mobilizing movements such as the so-called Arab Spring [1]. These platforms have provided a means for people to voice their opinions and mobilize large groups of individuals to take collective action.

Hence, the need to detect and analyse opinions in different domains such as politics, health, and marketing. Sentiment analysis is the task of automatically detecting attributes that express sentiment polarity and classifying a given text either into negative or positive in binary classification or into one of multiple classes in multi-class classification [2]. Although several works addressed sentiment analysis [3]–[5], most of these works have focused on treating texts in English, and thus studies provided in Arabic language still require more attention in order to take better advantage of the richness of Arabic language.

The main goal of this paper is to study the impact of combining two different types of deep learning classifiers to address sentiment analysis in Arabic. To this end, we have implemented a BiLSTM model and a GPT model. Furthermore, we have examined the influence of data quality on classification performance. Therefore, we have made use of three datasets of different sizes and language varieties.

The remainder of this paper is organized as follows. Section 2 gives a brief summary of the major studies on sentiment analysis in Arabic. In Section 3 we briefly discuss the methodology employed in this work. Section 4 discuss experimental results over the proposed architecture. Section 5 include conclusions and future work.

2. Related Work

This section provides a glance about works that studied sentiment analysis in Arabic. In general, researchers have made use of three types of models to address Arabic sentiment analysis: (1) basic models namely NB and SVM, (2) deep learning models like CNN and LSTM and (3) pretrained transformers.

Early works have studied Arabic sentiment analysis by making use of traditional machine learning techniques. In [6] the authors have developed an aspect-based system for Arabic text utilizing deep learning and three machine learning classifiers including SVM, RF, and LR. In addition, they investigated the effects of utilizing part of speech (POS) model and word embedding representation for Arabic sentiment analysis. For experimental work, they relied on

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Twitter's Rest API, to collect Saudi telecommunication companies' tweets. At first the collected dataset was consisted of 6182 tweets. Eventually after the preprocessing step they utilized a dataset consisted of 1068 tweets. Furthermore, they studied the influence of using n-gram method on predicting the polarity of a given text. This study has shown that combining machine learning classifiers with unigrams can yield to results significantly better than combining with bigrams. In another work [7] Atoum and Nouman addressed sentiment analysis of Jordanian dialect using SVM and NB. In this study they aimed to assign each tweet to a class based on three classes: positive, negative, and neutral. They investigated several techniques including stemming and n-grams. The best results are achieved with SVM classifier using light stemming. In addition, they proved that experiments on balanced datasets can improve accuracy score.

Recently multiple studies were conducted by making use of deep learning models, and most commonly used models in this field are CNN and LSTM. In this context, the author in [8] evaluated two deep learning models namely LSTM and CNN with two basic machine learning models including NB and SVM. The author addressed Arabic sentiment analysis in both binary and multi-class classification. For experiments, the proposed models are trained on diverse datasets. The research paper has demonstrated that deep learning techniques are more performant on large datasets. Whereas, traditional machine learning techniques attain better results on small datasets. Similarly, the authors in [9] introduced an Algerian corpus and compared different deep learning models against traditional machine learning models. Along with sentiment analysis, the proposed models have been trained to tackle emotion analysis task. For experiments, SVM and three deep learning models including CNN, LSTM, and MLP have been implemented. The best results were achieved by CNN model. Authors in [10] proposed a deep learning model using LSTM to perform categorize Arabic texts into two labels. The authors adopted an approach starting with a preprocessing step to clean data. Then, word embedding step follows to convert text to a numerical vector to be inputted into the next LSTM layer. Then, a softmax layer follows to output final predictions. The experiments indicated that LSTM are a good choice to address sentiment analysis task. The authors in [11] introduced their online system for Arabic sentiment analysis. They proposed a deep learning model based on CNN combined with LSTM. They conducted their experiments on three different datasets namely SemEval 2017 Task 4 [12], ASTD [13], and ArSAS [14], the findings of this study revealed that the proposed model increased accuracy score by 0.4% on SemEval 2017 dataset, as for ASTD dataset accuracy score has been improved by 0.1%, and for ArSAS dataset they reported an accuracy score of 92%.

More recently, transformer-based language models have gained momentum and attained state-of-the-art on several ANLP tasks, such as sentiment analysis [15], [16]. Particularly, in Arabic text classification such type of models has reported promising results. The authors in [17] investigated the most effective techniques exploited in Arabic sentiment analysis from basic machine learning models to complex deep learning models as well as more advanced language models such as hULMonA [18], BERT [19] and AraBERT [20]. Experiments have been conducted on multiple datasets namely SemEval 2017 Task 4, ArSAS and ASTD. The authors reported best accuracy score of 93% using AraBERT on ArSAS. The author in [21] explored two transformer-based language models including AraELECTRA [22] and AraBERT. They tackled two tasks: sentiment analysis and sarcasm detection. In sentiment analysis they performed a multiclass classification, where one of three classes (positive, negative, neutral) is assigned to each tweet. In sarcasm detection they conducted a binary classification in which a tweet is identified as sarcastic or not. In order to represent better the data, they opted for a methodology that starts with a preprocessing step in which data is cleaned and Farasa segmenter is applied [23]. Results showed that AraBERTv2-basevariant is more effective in sarcasm detection task. As for, AraBERTv0.2- large variant has proved to be more performant in sentiment analysis task.

3. Methodology

The proposed research methodology addresses Arabic sentiment analysis. It introduces a hybrid model that combines a generative pre-trained transformer with Bi-LSTM.

3.1. Data preprocessing

In sentiment analysis, the quality of data preprocessing impacts the performance of the proposed model, and it is just as crucial as the learning model's architecture. Data preprocessing involves cleaning and preparing text for classification. Generally, text data is one of the least structured forms of information available on the internet. Therefore, further processing is required to prepare this type of data for classification. Text cleaning is a fundamental step in text preprocessing, which includes the elimination of meaningless characters like punctuation, numbers, non-alphabetic characters, and any other characters whose absence has no impact on the sentence.

3.1.1. Noise removal

This step consists of the removal of punctuation, numbers, non-Arabic text, URL links, hashtags, emojis, extra characters, diacritics, and elongation of letters. The most commonly used cleaning technique for noise removal is regular expressions, which can filter out most unwanted text. The common operations performed for noise removal include:

- Removal of punctuation marks such as "'`÷×–—“…”!|+¦~{}',.؟":/،-][%^&*()_<>؛'"
- Removal of non-Arabic alphabets
- Removal of numbers
- Removal of emojis using a list of emojis frequently used on the internet
- Removal of diacritical marks such as: (ـَ) Fat-Ha, (ـِ) Kasra, (ـُ) Damma, (ـْ) Sokoun, and (ـّ) Shadda
- Removal of elongation known as tatweel, which can be represented by the stroke character (-) or the repetition of a letter. For example, the word "مرحبا" can be elongated in two forms:

Technique	*Form*
Using (-)	مرحبـــــا
Repeated letter	مرحباااااا

3.1.2. Stop words removal

The purpose of removing stop words is to eliminate frequently used words in a text that do not contribute much to the understanding of the document. By removing these less meaningful words from the text, we can focus on the most relevant words that carry more meaning, thereby reducing the vector's dimensionality that encodes the text.

Table 1. List example of Arabic stop words

سبعون	دولار	ثلاثة	اجل	أن
سبعين	ديسمبر	جمعة	أصبح	أنا
ست	ذلك	سنة	إلى	أنتم
ستة	رابع	حاليا	الذي	أنت
ستكون	سبعة	حتى	درهم	أنه
ستمئة	تم	حسب	به	أو
ستمائة	سابع	حين	تحت	أولئك
ستون	سبتمبر	خامس	تسعة	أيضا
ستين	سبحان	خلال	تلك	إذن

3.1.3. Tokenization

This represents the process of segmenting a given text to create a vector of individual elements called tokens. These tokens can come in form of characters, individual words, or even sentences. In this study, the tokenizer divides the text into words where separation of tokens is controlled by white characters. To represent sentences as numerical vectors, each word in the vocabulary is considered as a unique feature then assigned to a unique number. Fig. 1 shows an example of tokenization.

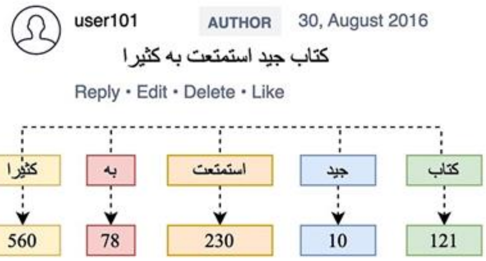

Fig. 1. Text tokenization example

3.2. Proposed Ensemble Model Architecture

In ensemble learning, multiple base models are combined together to compose a more robust model that can achieve better predictions. Recently, ensemble learning has gained momentum in the field of Arabic sentiment analysis owing this to its success to handle Arabic language challenges. Arabic sentiment analysis task is considered challenging due to the complexities that the language can offer. Ensemble learning can help overcome these challenges by combining different models that capture different aspects of the language. For example, one model can extract syntactic features while the other may extract lexical features.

Two main types of ensemble learning can be distinguished: simple ensemble learning and advanced ensemble learning. Simple ensemble learning includes three main methods: max voting, averaging and weighted averaging. On the other hand, advanced ensemble learning includes three different methods: bagging, boosting and stacking. In this study, an ensemble model based on averaging method has been implemented. It is a simple method used to create ensemble models. In this method, base models are trained on top of the same dataset. Then the outputs of each model are combined. One advantage of the averaging technique is that it can be used with the majority of base models and it is very simple to implement.

The structure adopted in this work consists of two different types of classifiers:

BiLSTM an advanced variation of LSTM model. In this type of model, we are allowed to process input sequences in both directions. This architecture gives the model access to two states including past information from the previous state and future information from the next state, facilitating a better understanding of context and dependencies within a sequence. BiLSTM is especially useful in sentiment analysis, where the context of a word plays a crucial role in determining its meaning.

AraGPT2 is a generative pre-trained language model proposed by Antoun et al. [24]. The model is trained using a collection of texts mostly written in Modern Standard Arabic (MSA), the model uses a self-attention mechanism to detect long-term dependencies between sequences over time. AraGPT2 has been widely applied in NLP tasks like text generation. For instance, it has been utilized in generating news, poetry, and other writing tasks. The model has four variants: base, medium, large, and xlarge.

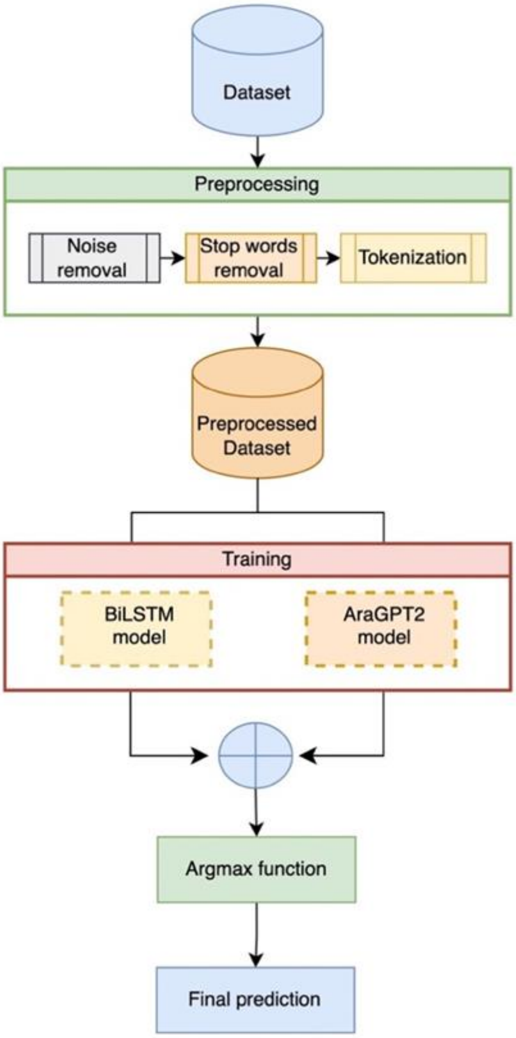

Fig. 2. BiLSTM-AraGPT2 model architecture

As illustrated in Fig. 2 the BiLSTM-AraGPT2 model focuses on combining two distinct base classifiers namely BiLTSM and AraGPT2. The first step is to train each base classifier separately on the same dataset. Once trained, each model produces a set of probabilities for each class label. These probabilities are then combined by adding the probabilities of both classifiers for the same class label. Finally, the argmax function is used to determine the class giving the highest predicted probability.

4. Experiments and Results

In this section, the used datasets and the findings of the conducted experiments will be discussed in detail

4.1. Data Collection

In this study we make use of three different datasets to experiment the proposed ensemble model. To this aim, we have selected three datasets of different sources, sizes and language varieties. First, the model is trained and tested on top of our balanced dataset introduced in a previous study [25], it is composed of 1299 books reviews written in MSA and annotated manually as either positive or negative. Secondly, we have utilized ASTD dataset [13] which is constituted of 10006 tweets. Lastly, the model is examined using Arabic gold standard Twitter [26] consisted of 8868 tweets labelled as: Negative, neutral, and positive.

Table 2. List example of Arabic stop words

Name	***Size***	***Language***	***Source***	***Reference***
Arabic book reviews (Goodreads)	1299	MSA	Goodreads	[25]
ASTD	10006	MSA/ DA	Twitter	[13]
Arabic Twitter corpus (Gold)	8868	MSA/ DA	Twitter	[26]

4.2. Results and discussions

This work introduces four models, two base models including a bidirectional LSTM and a language model called AraGPT. In addition, to investigate the impact of ensemble techniques we have proposed two ensemble models. The first is implemented using max voting ensemble technique Results and discussions

This work introduces four models, two base models including a bidirectional LSTM and a language model called AraGPT. In addition, to investigate the impact of ensemble techniques we have proposed two ensemble models. The first is implemented using max voting ensemble technique and the second is implemented using the average technique by adding the output probabilities of the two studied models. We investigate the performance of each model using the same training and testing set size which are set to 80% and 20% respectively. Several experiments were conducted to fine-tune the hyperparameters, aiming to obtain the most effective parameters for each model. The best configuration of all models is achieved with a batch size = 32 for both BiLSTM and AraGPT, and the optimal number of epochs is 7 for the BiLSTM based model and 3 for AraGPT based model. Furthermore, we used a sequence length of 30 for BiLSTM model and 128 for the AraGPT model.

Table 3 illustrates the experimental results using BiLSTM, AraGPT2, Max voting, and our proposed ensemble model.

It can be clearly seen from Fig.3, that our proposed ensemble model has achieved remarkable results and ranked first on the majority of datasets. On unbalanced datasets, the model improved the accuracy by 2% on ASTD and 1% on Gold. On the other hand, on balanced datasets the model improved accuracy on our dataset with by approximately 7%. Whilst on ASTD our proposed model outperformed the other models by a narrow margin. However, the model fell short to improve the performance on balanced Gold dataset.

Following an extensive examination through the misclassified texts, we have identified several factors that have direct impact on the models' performance. First, both datasets ASTD and Gold are written in both MSA and multidialectal Arabic, which negatively affects the model's performance compared to when trained on MSA texts only. In addition, an examination of Gold dataset has revealed many texts with typing errors. Some examples of the misclassified texts showing the typing errors in the texts are given in Table 4. On the same dataset we have also found that some misclassified texts can hold mixed sentiments, which can impact the overall sentiment of the sentence (Table 5 shows examples of such texts). Similar to the Gold dataset, texts with mixed sentiments are also present in the ASTD dataset as shown in figure 6. Furthermore, an examination of the ASTD dataset identified some texts with incorrect labels (Table 6 provides examples). Given these statistics, it can be said that incorrect labelling has a considerable influence on classification performance.

Table 4. Texts with typing errors on Gold dataset

Text	***Dataset's label***	***Predicted label***
لوحة رائعه رسمها التنان العالمي بوب روس والذي يصت تيها حالته وهو طتل حيث ترك وذهب ليبيع الحلوي بجوار المدرسة	Positive	Negative
تبا لكل مؤلمعطر الحرت استتزني تقاطعتكمولمجارتكم ممتنة اناطبتم وطاب مساءكم خاليا من كل	Negative	Positive
عندما يتقن اللعبه الاعلاميه ويتدخل تي إتخاذ القرارات ويكون تعالا تي اللجان سيهيمن على البطولات .. خارج الملعب متقود!العمل	Positive	Negative

Table 5. Texts with mixed sentiments on Gold dataset

Text	***Dataset's label***	***Predicted label***
شكلها هتولع	Positive	Negative
مش هتقدر تغمض عينيك هه	Positive	Negative
اللهم انصر اهل العراق من السنه المضطهدينمن والمجوس	Negative	Positive

Table 6. Texts with mixed sentiments on ASTD dataset

Text	***Dataset's label***	***Predicted label***
البقية فى حياتك كان راجل عظيم	Negative	Positive
وزير الغلابة #باسم_عودة معتقل ف سجون العسكر ل #افضل_منتج_لاكرم_شعب #انا_مش_رقم #انتفاضة_السجون	Positive	Negative
هو ممكن ت #نزل_صلاح :(#ليلة_الابطال	Negative	Positive

Table 7. Texts with incorrect labels on ASTD dataset

Text	***Dataset's label***	***Predicted label***
خلق_جميل الشعور بالغير#	Negative	Positive
مصر حسمت هويتها منذ مئات السنين بأنها دولة مسلمة وعربية وقبل ذلك بأنها أم الدنيا التى تفتح أذرعتها للجميع وتتواصل مع كل الحضارات	Negative	Positive
صحفي ألماني يروي تفاصيل ليلة مرعبة من التعذيب والإهانة بين المعتقلين المصريين في الأقسام والسجون	Positive	Negative
و انتي طيبة يا حنان و كل الناس بخير (:	Negative	Positive
لا إله إلاَّ اللَّه وَحْدَهُ لا شرِيكَ لَهُ، لهُ المُلكُ ، وَلهُ الحَمْدُ ، وَهُوَ عَلى كُلِّ شَيءٍ قَدِيرٌ #غرد_بذكر_الله #كنز_المسلم	Negative	Positive

Table 3. Summary of results

Dataset	*Evaluation Metric*	*BILSTM*	*ARAGPT2*	*MAX VOTING*	*SUM*
Goodreads	Accuracy	0.8031	0.8185	0.8069	**0.8764**
	Precision	0.7619	0.8649	0.9239	0.8810
	Recall	0.8750	0.7500	0.6641	0.8672
	F1-Score	0.8145	0.8033	0.7727	0.8740
ASTD balanced	Accuracy	0.7469	0.8062	0.7531	**0.8063**
	Precision	0.7588	0.8690	0.8814	0.8452
	Recall	0.7633	0.7456	0.6154	0.7751
	F1-Score	0.7611	0.8025	0.7247	0.8086
ASTD Unbalanced	Accuracy	0.7726	0.8390	0.7968	**0.8571**
	Precision	0.6697	0.7823	0.8551	0.8319
	Recall	0.4867	0.6467	0.3933	0.6600
	F1-Score	0.5637	0.7080	0.5388	0.7361
Gold balanced	Accuracy	0.7407	**0.8433**	0.8148	0.8348
	Precision	0.7304	0.8457	0.9054	0.8432
	Recall	0.8054	0.8595	0.7243	0.8432
	F1-Score	0.7661	0.8525	0.8048	0.8432
Gold unbalanced	Accuracy	0.7394	0.8582	0.8280	**0.8688**
	Precision	0.5294	0.7088	0.8315	0.7384
	Recall	0.5192	0.8269	0.4744	0.8141
	F1-Score	0.5243	0.7633	0.6041	0.7744

5. Conclusions and Future Work

Ensemble learning is a robust technique primarily introduced to deal with learning mistakes and achieve higher accuracy by combining the strengths of different single models. To investigate the impact of ensemble learning techniques this study proposed a simple ensemble technique that adds final outputs of each model. For comparative experiments we have implemented ensemble model by making use of max voting technique. To measure the performance of these models we have opted for three different Arabic datasets each with a different size and challenges.

Experiments have confirmed the efficiency of our proposed ensemble model in Arabic text classification task. The model has improved the performance by 7% on our dataset. However, the model has only marginally improved the accuracy score on ASTD and Gold datasets. This low performance is associated with data quality. After a thorough examination of misclassified texts, we have identified several challenges on ASTD and Glod datasets including incorrect labelling, mixed sentiments and typing errors. This study has demonstrated that input data quality can substantially impact classification performance.

In the future, we wish to investigate more language models on different types of datasets to observe the performance of the used models.

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