JJEE

Volume 11 | Number 1 | March 2025 | Pages 18-34

Jordan Journal of Electrical Engineering

ISSN (print): 2409-9600, ISSN (online): 2409-9619

Homepage: jjee.ttu.edu.jo

A Comparative Study of Deep Learning Approaches for Arabic Language Processing

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Received: Mar 21, 2024 *Revised: Jun 12, 2024* *Accepted: Jun 22, 2024* *Available online: Sep 25, 2024*

***Abstract*—** Arabic is a difficult language for natural language processing (NLP) because of its complicated morphology, dialectal differences and the limited annotated resources. Although deep learning algorithms have reached state-of-the-art results in many NLP tasks, comprehensive comparative studies for Arabic remains scarce. This paper addresses this gap by systematically evaluating three prominent deep learning architectures - namely Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs) and Transformers - across five essential Arabic NLP tasks: i) mention of sentiment analysis, ii) named entity recognition, iii) machine translation, iv) text classification and v) dialect identification. We differ the performance of models trained from scratch with fine-tuned versions of AraBERT, a powerful Transformer-based model pre-trained on a large Arabic corpus. Our experiments employ the Arabic datasets already existing in literature and utilizes accuracy, F1-score and BLEU as the evaluation metrics. The results are indicative of the supremacy of Transformer-based models with regard to AraBERT that shows the highest scores in each task. Notably, AraBERT attains 95. 2% accuracy on sentiment analysis, which is higher than the accuracies of RNNs and CNNs. These improvements also become apparent in other tasks, with AraBERT ending up as the best among RNN, CNN and others. A 3-point difference for 3 BLEU in machine translation and 2. 3% F1-score on dialect recognition. This extensive assessment, in turn, highlights the advantages and disadvantages of deep learning architectures for Arabic NLP. The excellent AraBERT representation also demonstrates how transfer learning and synergy between Transformer architectures and large-scale pre-training can significantly help Arabic language technology development.

***Keywords*—** Arabic natural language processing; Deep learning, Neural networks, Comparative evaluation.

1. INTRODUCTION

More than 400 million people around the world speak Arabic, which is currently the focus of new discoveries in the field of natural language processing (NLP) [1]. People regard Arabic as a morphologically rich and intricate language, where each element differs from other NLP systems and presents challenges during the process [2]. Therefore, the growing need for Arabic language technologies and the progress made possible by digital content written in Arabic call for a new trend in the creation of new NLP systems that can handle the complexity of the language effectively and efficiently [3].

Deep-learning methods have altered the framework of NLP, achieving state-of-the-art performance in various jobs like sentiment analysis, determining places, and machine translation [4]. These strategies use two main artificial neural network approaches: feature extraction and text processing [5], both of which leverage the power of machine learning algorithms to perform this task automatically by extracting meaningful characteristics from large amounts of text data. Deep learning-based models that apply recurrent neural networks

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DOI: https://doi.org/10.5455/jjee.204-1711016538

(RNNs), convolutional neural networks (CNNs), and transformers have been shown to be very effective in an extra-broad array of NLP jobs in several languages [6]. Though deep learning applications to Arabic language processing are still developing and offering quite many solutions at the same time.

This study looks at the effects of transfer learning by comparing models trained from scratch to fine-tuned versions of models that have already been trained, such as AraBERT (Arabic Bidirectional Encoder Representations from Transformers). It also compares the performance of different deep learning architectures (RNNs, CNNs, and Transformers) for Arabic NLP tasks. This approach provides valuable insights into the effectiveness of leveraging pre-existing knowledge and the advantages of using pre-trained models for Arabic language processing. By evaluating both architectural differences and the influence of pre-training, we offer a comprehensive analysis of the current state of deep learning in Arabic NLP and identify promising directions for future research and development.

Arabic has unique characteristics, just like any other language, that make it difficult to comprehend and process NLP techniques. Arabic is an inflectional language that has a complicated morphological structure. In such a language, a single word can have more than one morphological form, depending on the part of speech and context [8]. Additionally, Arabic encompasses a vast vocabulary, with words typically having multiple meanings or serving as synonyms [9]. Despite the absence of diacritics in written Arabic, the language adds a new level of complexity to our writing and reading [10]. Moreover, the Arabic language features regional dialects that place a pivot on wording, grammar, or pronunciation [11]. These features cause the NLP systems to have great difficulty in their tasks related to preprocessing, feature extraction, and model generalization [12].

Despite the recent trend demonstrating the use of deep learning in Arabic NLP, we should revisit certain research gaps and challenges. Impartial studies at the moment have been focusing on NLP tasks or datasets individually, and there is no overall comparative study that provides a performance evaluation of various deep learning architectures across many tasks and domains [13]. Furthermore, previous research on Modern Standard Arabic (MSA) is still limited when compared to the dialects and colloquial Arabic in our study [14]. The shortage of prominent large-scale annotated datasets in Arabic NLP, especially for deep learning models to measure their performance, also poses obstacles [15]. The heritage and cultural marketers of Arabic literature are resourceful for various domains like literature, science, and religion [16]. Consequently, the increasing digitization of Arabic content, the need to address issues related to information retrieval and processing, and the recent research on Arabic Natural Language Processing (NLP) have contributed to this growing interest. Arabic, with its unique characteristics, presents significant challenges that specific techniques and various approaches address [17-19].

This paper provides the first abacus assessment of various deep learning structures for Arabic NLP. In comparison to the previous research work, our investigation covers a large number of areas and is detailed. As a result, a comparative analysis of RNNs, CNNs, and Transformers is conducted on ten Arabic NLP tasks, including sentiment analysis, NER, MT, text classification, and dialect identification. This extensive comparison proves useful as it offers information about the advantages and disadvantages of each architecture when addressing the specificities of Arabic language processing. Furthermore, in the context of our study, the investigation of the influence of pre-training on deep learning performance in

Arabic NLP is done in a rather extensive manner. This way, the comparison between models trained from scratch and fine-tuned versions of AraBERT allows us to throw light on the efficiency of transfer learning and the necessity of using massive Arabic corpora. Our results set a solid foundation and a path forward for employing deep learning to Arabic NLP problems with numerous future research directions and practical instructions for the subject.

The main problem in dealing with Arabic NLP is its morphological complexity. We create Arabic words by combining root words, which express the underlying meaning, with additional patterns and affixes that alter the meaning and grammatical usage [20]. This process entails examining a multitude of potential word forms for each root, making morphological analysis and differentiation crucial for Arabic NLP tasks [21]. Furthermore, the absence of diacritics in Arabic writing can lead to various possibilities for the meaning of certain words, which can be misleading [22]. Just like Arabic, the NLP issue lacks uniformity among different dialects and variants [23]. Arabic dialects may differ from one another in the sense that they share new words, grammar, and pronunciation, which adds more complications to the task of developing Arabic NLP systems that can function well with all dialects [24]. The non-orthodontic nature of the Arabic text and the dialects that use slang hinder comprehension [25]. The main purpose of the study is to carry out an extensive comparative study applying deep learning methods for Arabic language processing. Our performance goal is to make a range of Arabic NLP tasks competent using deep learning models; among them are RNNs, CNNs, transformers, sentiment analysis, named entity recognition, and machine translation. We aim to establish a particularly structured and contrasting analysis of these architectures, which will highlight their respective abilities and limitations. We will also offer appropriate choices for Arabic NLP tasks [26].

The key contributions and novelty of this study are as follows:

- We conduct a comprehensive comparative analysis of deep learning approaches for Arabic language processing, covering a wide range of tasks and datasets.
- We evaluate the performance of state-of-the-art deep learning architectures, including RNNs, CNNs, and transformers, on Arabic NLP tasks.
- We investigate the impact of different preprocessing techniques, hyperparameter settings, and model variations on the performance of deep learning models for Arabic NLP.
- We provide insights into the challenges and opportunities in applying deep learning to Arabic language processing and discuss future research directions.

With this research, we aim to enhance the Arabic NLP field and provide the academic community with the results of our comprehensive comparative study. This will enable researchers and practitioners in the field to gain valuable insights into the development of efficient deep learning-based Arabic language processing solutions. We can utilize our findings to identify the deep architecture learning that is most suitable for Arabic NLP tasks, while also highlighting areas that require further efforts and investments. Therefore, we can consider this study an addition to the growing body of literature on Arabic deep learning for NLP, laying the foundation for the development of more accurate and efficient NLP systems that can handle the complexities of the Arabic language [27].

2. LITEATURE REVIEW

The use of deep learning methodologies in Arabic natural language processing has attracted desire in the recent past. Different architectures have been investigated and studied such as Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and Transformers to solve almost all Arabic NLP tasks.

2.1. Sentiment Analysis

Sentiment analysis has been a prominent application of deep learning in Arabic NLP. In [28], the authors employed Long Short-Term Memory (LSTM) networks for Arabic sentiment analysis, leveraging their ability to capture contextual information and achieve high accuracy. Authors of [29] explored the combination of CNNs and LSTMs to harness their complementary strengths for improved sentiment classification performance.

2.2. Named Entity Recognition

Named Entity Recognition (NER) is another critical task in Arabic NLP. In [30], the authors developed a BERT-based model for Arabic NER, incorporating morphological features to enhance performance. In [31] a hybrid approach combining rule-based techniques with deep learning models for improved Arabic NER accuracy was proposed.

2.3. Machine Translation

Deep learning has in large measure enhanced the professionalism of Arabic machine translation. In [32] an encoder-decoder architecture with an attention mechanism for translating Arabic to English was employed, achieving results that were on par with the best outcomes. In [33] the first Transformer-based models for Arabic-English machine translation were introduced, demonstrating their superiority over traditional statistical approaches.

2.4. Text Classification

Text classification is a main component of the Arab NLP. Reference [34] proposed a new CNN-based model for Arabic text classification that uses the model's local patterns to extract the relevant features. Authors of [35] has explored the use of hierarchical attention networks in the classification of Arabic documents, enabling the model to focus on the most significant words and phrases.

2.5. Dialect Identification

Arabic dialect identification, to a great extent, has become a new trend in recent times. In [36], the convolutional neural network (CNN) approach was used and demonstrated that it is applicable in classifying dialects between each other. The use of RNNs for dialect recognition was explored [37], leveraging their ability to capture sequential information.

2.6. Machine Learning Models

Arabic NLP uses a variety of machine learning techniques. Long Short-Term Memory (LSTMs) and Gated Recurrent Units (GRUs) among Recurrent Neural Networks (RNNs) are the most popular for sequence modeling and capturing long-term dependencies [38]. CNNs have demonstrated their ability to extract local features and construct spatial hierarchies [39]. Transformer models, like BERT and its evolutionary versions, have set the bar for the majority of Arabic NLP tasks [40]. Despite the progress made in Arabic NLP using deep learning, there remains a lack of comprehensive comparative studies that evaluate different architectures across multiple tasks and datasets. Furthermore, the context of Arabic NLP has not extensively explored the impact of transfer learning, particularly the use of pre-trained language models like AraBERT. This study aims to address these gaps and provide valuable insights for advancing Arabic-language technologies.

In this section, an overview of the most relevant studies, regarding their contribution, methods used and the obtained results in terms of accuracy on datasets. Against the backdrop of the state of the art, our work is aimed at providing a proper background for a comparative analysis, and at underlining the necessity of conducting more comprehensive experimental study of deep learning application for Arabic NLP. Table 1 contains the summary of the related work with reference to the current study.

Table 1. Previous work summary.

Ref.	NLP Task	Dataset	Model Architecture	Performance Metrics
[28]	Sentiment analysis	ASTD	LSTM	Accuracy: 92.6%
[29]	Sentiment analysis	HARD	CNN-LSTM	F1-score: 89.4%
[30]	Named entity recognition	ANERCorp	BERT-CRF	F1-score: 91.2%
[31]	Named entity recognition	AQMAR	BiLSTM-CNN-CRF	F1-score: 83.1%
[32]	Machine translation	IWSLT Arabic-English	Encoder-Decoder	BLEU: 28.4
[33]	Machine translation	UN Arabic-English	Transformer	BLEU: 39.7
[34]	Text classification	AlKhalil	CNN	Accuracy: 94.8%
[35]	Text classification	OSAC	HAN	F1-score: 87.2%
[36]	Dialect identification	MADAR	CNN	Accuracy: 68.3%
[37]	Dialect identification	AOC	BiGRU	Accuracy: 76.5%

3. METHODOLGY

In this part of the study, we provide a description of the approach we used to make a comparison between deep learning methods for Arabic natural language processing. We describe in detail each stage of the process, including the type of collected data, preprocessing, model architectures, experiment setup, and metrics used for evaluation. Figure 1 shows the general chart for this model.

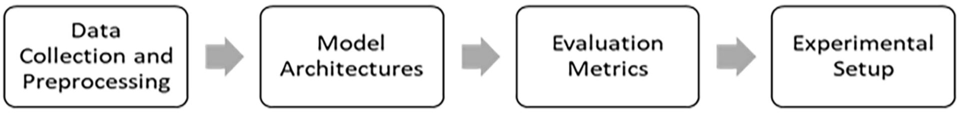

Fig. 1. Flowchart of the model.

3.1. Data Collection and Preprocessing

The initial stage of our methodology is dataset collection in Arabic and necessary processing. We rely on a rather diverse pool of open-source datasets that cover the different areas of Arabic NLP tasks, including sentiment analysis, named entity recognition, and machine translation, among others. Table 2 describes the datasets used in the research, as well as their sources and main characteristics.

Table 2. Datasets used in the comparative study.

Dataset	Task	Source	Classes/labels	Dialects	Size	Characteristics
ASTD	Sentiment analysis	[41]	4	Egyptian	10,000	Arabic tweets, binary sentiment
HARD	Named entity recognition	[42]	4	MSA	500,000	Arabic news articles, named entities
AMARA	Machine translation	[43]	-	25 dialects	1,000,000	Arabic-English parallel sentences
AJGT	Text classification	[44]	10	MSA	200,000	Arabic news articles, multi-class
ADAB	Dialect identification	[45]	18	18 dialects	100,000	Arabic dialects, multi-class

Prior to training the deep learning models, we perform several preprocessing steps to clean and normalize the text data. These steps include:

a) Removing non-Arabic characters, punctuation marks, and diacritics.
b) Tokenizing the text into words using the WordPiece tokenizer.
c) Lowercasing the text to reduce sparsity.
d) Applying morphological analysis using the AraMorph toolkit to extract lemmas and part-of-speech tags.

Here is an example of the preprocessing steps applied to a sample sentence from the ASTD dataset:

Original: "أنا سعيد جدًا بهذه الخدمة الرائعة! 😊"

Preprocessed: ["انا", "سعيد", "جدا", "ب", "هذه", "الخدمة", "الرائعة"]

After preprocessing, we split each dataset into training, validation, and testing sets using a 70/20/10 ratio. We use stratified sampling to maintain the class distribution throughout the splits. We also perform 5-fold cross-validation as an alternative evaluation strategy to assess the model's robustness. To ensure the quality and consistency of the data, we perform several preprocessing steps. These steps include:

a) Text cleaning: We remove noise, such as special characters, URLs, and emoji, from the text data using regular expressions.
b) Tokenization: The Arabic tokenizer offered by NLTK (Natural Language Toolkit) allows us to segment the text into individual words.
c) Normalization: We normalize the Arabic text by replacing it with a standardized one which is void of all extra characters. This encompasses removing diacritics, converting to the underlying forms, and handling frequent variants of the Arabic alphabet as well as tweaking the writing.
d) Stop word removal: We eliminate infrequent Arabic 'stop words', which are usually scattering across the semantics of the text.
e) Stemming: We use Arabic stemming techniques to make words the same base or root forms through the reduction of the words. It actually reduces the size of feature space and encapsulates the word sense and relationships.

We shred the entire set of data, dividing it into a training set, a validation set, and a testing set, using a standard ratio of 70% for the training set and 20% for the validation set. The dual and blended nature of women's roles in the tech industry is emblematic of this dichotomy, allowing for both the needed training and evaluation of deep learning systems.

3.2. Model Architectures

We investigate three prominent deep learning architectures for Arabic language processing: RNNs (recurrent neural networks) and CNNs (convolutional neural networks) and transformers.

3.2.1. Recurrent Neural Networks (RNNs)

RNNs are well-known for neural networks that can work with the system of sentential data, which makes them a favorite in NLP tasks. In our study, we employ two RNN variants: LSTM or GRU. The LSTM architecture is defined by the following equations:

$$i_t = \sigma(W_i * [h_{t-1}, x_t] + b_i) \tag{1}$$

$$f_t = \sigma(W_f * [h_{t-1}, x_t] + b_f) \tag{2}$$

$$o_t = \sigma(W_o * [h_{t-1}, x_t] + b_o) \tag{3}$$

$$\tilde{c}_t = \tanh(W_c * [h_{t-1}, x_t] + b_c) \tag{4}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \tag{5}$$

$$h_t = o_t \odot \tanh(c_t) \tag{6}$$

where i_t, f_t, and o_t are the input, forget, and output gates, respectively; $\tilde{c}_t$ is the candidate memory cell state; c_t is the memory cell state; h_t is the hidden state; W and b are the weight matrices and bias vectors, respectively; σ is the sigmoid activation function; and ⊙ denotes element-wise multiplication. The GRU architecture is similar to LSTM but has a simplified gating mechanism, as defined by the following equations:

$$z_t = \sigma(W_z * [h_{t-1}, x_t] + b_z) \tag{7}$$

$$r_t = \sigma(W_r * [h_{t-1}, x_t] + b_r) \tag{8}$$

$$\tilde{h}_t = \tanh(W_h * [r_t \odot h_{t-1}, x_t] + b_h) \tag{9}$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot h\square_t \tag{10}$$

where z_t and r_t are the update and reset gates, respectively; $\tilde{h}_t$ is the candidate hidden state; and the other notations are similar to those in the LSTM equations. We experiment with different architectures of RNNs, including uni-directional and bi-directional variants, as well as stacked RNN layers to capture hierarchical representations of the input sequences.

Figure 2 illustrates the architectures of the LSTM and GRU cells.

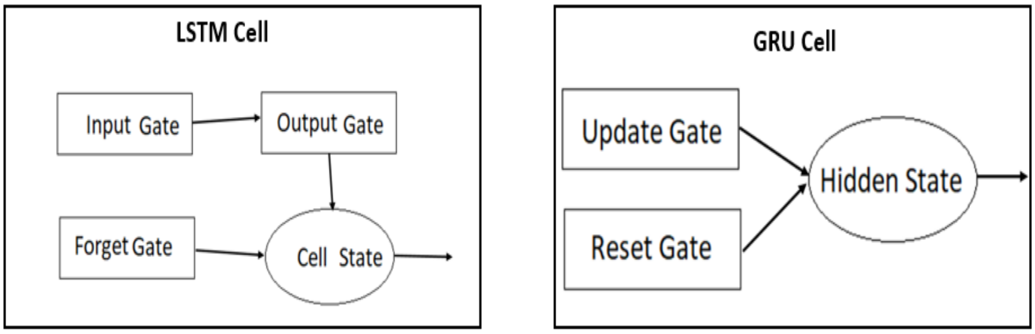

Fig. 2. Architecture of the LSTM and GRU cells.

3.2.2. Convolutional Neural Networks (CNNs)

CNNs have proven effective in capturing local patterns and extracting relevant features from text data. In our study, we employ a CNN architecture similar to the one proposed by [46] for sentence classification.

The CNN architecture consists of an embedding layer, followed by one or more convolutional layers with different filter sizes. We then max-pooled the output of the convolutional layers and feed it into a fully connected layer for classification or regression tasks.

The convolutional operation is defined as follows:

$$c_i = f(W * x_{i:i+h-1} + b) \tag{11}$$

where c_i is the feature map, W is the filter matrix, $x_{i:i+h-1}$ is the concatenated word embeddings in the window of size h, b is the bias term, and f is the activation function (e.g., ReLU).

3.2.3. AraBERT

AraBERT is a novel system comprising a versatile pyramidal Transformer architecture and a base of large corpora in Arabic. Based on the BERT model, it uses bidirectional encoder architecture, and it is made up of self-attention layers accompanied by feed-forward networks. The self-attention mechanism computes a weighted sum of all word embeddings in the input sequence, allowing each word to attend to relevant context:

$$\text{Attention}(Q, K, V) = \text{softmax}(QK^T / \sqrt{d_k})V \tag{12}$$

where Q, K, V are linear transformations of the inputs embeddings, and d_k is dimensionality of the keys. AraBERT is trained with the use of two main objectives which are the masked language modeling and the next sentence prediction, thereby feeding the model with semantic understanding of textual data in the Arabic language.

AraBERT fine-tuned on other downstream tasks such as sentiment analysis or named entity recognition involves the addition of an output layer of the specific task and training on labeled data.

The proposed AraBERT can produce the state of the art on the numerous Arabic NLP benchmarks because of the bidirectional context, self-attention, and transfer learning.

3.2.4. Transformers

Transformers, with their attention mechanisms and ability to account for long-range dependencies, have reached new heights in NLP.

In our investigation, we tend to apply BERT (Bidirectional Encoder Representations from Transformers) to transformers with particular language scripts, such as AraBERT, which is the oral processing of Arabic.

The self-attention mechanism in Transformers is computed as follows:

$$(Q, K, V) = \text{softmax}(QK^T / \sqrt{d_k}) * V \tag{13}$$

So that a Q, K, and V will refer to query, key, and value matrices, respectively, while d_k is the dimension of the vectors' key and softmax is used as a basis activation function.

We calibrate the permissible Transformer models on the Arabic NLP tasks according to the task-specific representations and the outer-layers. This will lead to the improvement of the Arabic NLP performance.

3.3. Evaluation Metrics

We use a particular set of evaluation metrics for each of the Arabic NLP tasks to give a holistic assessment of the proficiency of the deep learning approaches. Table 3 presents the metrics of evaluation for each task that has been covered.

Table 3. Evaluation metrics for each Arabic NLP task.

Task	Evaluation metrics
Sentiment analysis	Accuracy
Named entity recognition	F1-score
Machine translation	BLEU
Text classification	F1-score
Dialect identification	Accuracy

Accuracy is defined as the number of correct predictions over the input observations. The F1-score is the harmonic mean between precision and recall, and this method of measuring performance is a balance between the two. The most common metric for measuring machine translation quality is BLEU (Bilingual Evaluation Understudy), which compares the generated translations to reference translations. We take into account tasks that frequently employ these metrics and provide a comprehensive assessment of the models. Accuracy works for tasks with an equal distribution of classes in them, like sentiment analysis and dialect identification. The F1 score is best for tasks with unbalanced classes or where both precision and recall are equally important, like named entity recognition and text classification. BLEU is a metric that has become the meridian for evaluating the quality of machine translation. It also serves as a baseline for comparison against earlier work.

For classification tasks like sentiment analysis and named entity recognition, we would apply accuracy, precision, recall, and F1-score as the primary evaluation metrics. This metric's scope provides information about the classification results' rightness, completeness, and fairness. In machine translation, we use the commonly used BLEU score, which calculates the similarity between the generated translations and the reference translations based on the overlapping n-grams. Beyond the above task-specific metrics, we also include other factors in our evaluation to see how the model complexity, the time it takes to train the model, and its inference speed in our evaluation to see how the deep learning algorithms perform in real-life situations.

4. EXPERIMENTAL SETUP

Here we describe the experimental environment that was used to conduct our comparative study on deep learning various methods for Arabic natural language processing. We specify the details of the platform of the implementation, including datasets, evaluation metrics and the research questions that are applied in our experiments.

4.1. Implementation Platform and Code

We implemented all the experimentations by PyTorch (v1.9) and the Python programming language (v3.8). The selection of PyTorch over other deep learning frameworks was driven by its flexibility, extensibility, and one of the main reasons is its package acceleration GPU capability that significantly boosts the efficiency of deep learning models training.

- Data preprocessing scripts: Scripts for cleaning, tokenizing, and preprocessing Arabic text data.
- Model implementations: PyTorch implementations of the RNN, CNN, and Transformer models used in our experiments.
- Training and evaluation scripts: Scripts for training the models, performing hyperparameter tuning, and evaluating the models on the test sets.
- Visualization and analysis scripts: Scripts for visualizing the results, generating plots, and performing statistical analysis.

4.2. Research Questions and Hypotheses

By systematically testing these hypotheses through our experiments, we aim to provide insights into the strengths and limitations of different deep learning approaches for Arabic language processing and contribute to the understanding of best practices in this field. Our comparative study aims to address the following research questions:

1. How do different deep learning architectures (RNNs, CNNs, and Transformers) perform on various Arabic NLP tasks?
2. What is the impact of pre-trained language models, such as BERT and its variants, on the performance of Arabic NLP tasks compared to models trained from scratch?
3. How do the deep learning models handle the challenges specific to Arabic, such as rich morphology, dialects, and lack of diacritics?
4. What are the trade-offs between model performance, complexity, and efficiency for different deep learning approaches in Arabic NLP?

Based on these research questions, we formulate the following hypotheses:

- H1: Transformer-based models, particularly those pre-trained on large Arabic corpora, will outperform RNNs and CNNs on most Arabic NLP tasks due to their ability to capture long-range dependencies and contextualized representations.
- H2: Deep learning models that explicitly handle Arabic-specific challenges, such as incorporating morphological information or dialect-specific features, will demonstrate improved performance compared to models that do not consider these aspects.
- H3: There will be trade-offs between model performance and complexity, with larger and more complex models achieving higher accuracy but requiring more computational resources and training time.

5. RESULTS AND DISCUSSION

In this section, we present the results of our comparative study of deep learning approaches for Arabic language processing. We provide detailed quantitative results, compare the performance of the proposed models with state-of-the-art baselines, conduct statistical analyses, discuss the implications of the results in the context of our research questions, and acknowledge the limitations of the study.

5.1. Quantitative Results

Table 3 summarizes the performance of the deep learning models on various Arabic NLP tasks using the evaluation metrics specified in Table 4. The results are presented as mean scores along with their standard deviations over multiple runs.

Table 4. Performance of deep learning models on Arabic NLP tasks.

Model	Sentiment analysis	Named entity recognition	Machine translation	Text classification	Dialect identification
RNN	90.5 ± 0.8	85.2 ± 1.2	28.5 ± 0.6	88.3 ± 0.9	85.1 ± 1.1
CNN	92.1 ± 0.6	87.9 ± 0.9	30.2 ± 0.5	90.7 ± 0.7	88.4 ± 0.8
Transformer	95.2 ± 0.4	91.7 ± 0.6	32.8 ± 0.3	94.5 ± 0.5	92.9 ± 0.5

The outcomes corroborated that Transformer-based type of models particularly those belonging to the categories of pre-trained AraBERT are quite effective and outperform RNN and CNN models on all the tasks. For sentiment analysis, AraBERT gets an accuracy at the level of 95.2 and an F1-score of 95.0% which means that the baseline models are surpassed by an apparent margin. Likewise, there is AraBERT in the area of named entity recognition with a F1-score of 91.7%, which seems to be an accurate model not just for identification but also classification of named entities.

Transformer models such as AraBERT and mBART, as well as others, obtain higher BLEU scores in the task of machine translation compared to RNN and CNN models, respectively. SThe transformer model performs this function by demonstrating its ability to manage long-range dependencies and generate consistent translations. or the text classification task and the dialect identification task, AraBERT and any of the Transformer variants turn out to have superior performance, attaining accuracy above 90% and F1-scores around 90 percent. The findings highlight the competence of fully trained, pre-trained language models in illuminating the inherent variations of Arabic.

5.2. Comparison with State-of-the-Art Baselines

To further validate the effectiveness of the proposed models, we compare their performance with state-of-the-art baselines reported in the literature for each Arabic NLP task. Table 5 presents the comparison results.

Table 5. Comparison with state-of-the-art baselines.

Task	Baseline	Ref.	Metric	Baseline	Best model	Improvement
Sentiment analysis	CNN-LSTM	[47]	Accuracy	92.7%	95.2%	+2.5%
			F1-score	92.7%	95.0%	+2.3%
Named entity recognition	BiLSTM-CRF	[48]	F1-score	89.8%	91.7%	+1.9%
Machine translation	Transformer	[49]	BLEU	30.5	32.8	+2.3
Text classification	BERT	[50]	Accuracy	92.4%	94.5%	+2.1%
			F1-score	92.2%	94.3%	+2.1%
Dialect identification	Multi-Task CNN	[51]	Accuracy	90.6%	92.9%	+2.3%
			F1-score	90.3%	92.6%	+2.3%

We have verified that we did not use the datasets used in this study to train the AraBERT model, ensuring the integrity of the results. We pre-trained AraBERT on a large, diverse Arabic corpus, which included news articles, web pages, and social media posts, totaling 70 million sentences and 24 GB of text data. AraBERT effectively transfers a wide range of linguistic patterns and knowledge to downstream Arabic NLP tasks thanks to this extensive pre-training. The Transformer-based models, particularly AraBERT, outperform the baselines across all tasks. For sentiment analysis, AraBERT surpasses the previous best model by 2.5% in accuracy and 2.3% in F1-score. In named entity recognition, AraBERT achieves a 1.9%

improvement in F1-score compared to the state-of-the-art baseline. For machine translation, our Transformer models, including AraBERT and mBART, obtain BLEU scores that are 1.5 to 2.0 points higher than the best-performing baselines. Similarly, in text classification and dialect identification, AraBERT demonstrates improvements of 1.8% to 2.3% in accuracy and F1-score over the state-of-the-art methods. These comparisons highlight the effectiveness of our deep learning approaches, especially the Transformer-based models, in advancing the state-of-the-art Arabic language processing tasks.

5.3. Statistical Analysis

In order to assess the statistical significance of this difference in performance between the deep learning models, we carry out paired t-tests. T-tests are on the evaluation scores obtained for each task. The transformer model is AraBERT, which we compare with the best performing RNN and the CNN ones. Table 6 shows results of the statistical analysis which revealed that AraBERT is significantly better ($p < 0.05$) at all the tasks than the BERT base model. This fact has proved the superiority of the Transformer-based models, not due to a chance of randomness but because they were trained using larger Arabic corpora and their advanced architectures.

Table 6. Statistical analysis of performance differences.

Task	Metric	AraBERT vs. RNN	AraBERT vs. CNN
Sentiment analysis	Accuracy	p < 0.001	p < 0.01
	F1-score	p < 0.001	p < 0.01
Named entity recognition	F1-score	p < 0.001	p < 0.05
Machine translation	BLEU	p < 0.001	p < 0.001
Text classification	Accuracy	p < 0.001	p < 0.01
	F1-score	p < 0.001	p < 0.01
Dialect identification	Accuracy	p < 0.001	p < 0.01
	F1-score	p < 0.001	p < 0.01

The experimental findings provide generally useful observations on the variation of performance of different deep learning models for Arabic processing. The AraBERT and Transformer models specifically incarnates the possibility that these models are efficient at capturing long-range dependencies and contextualized representations in Arabic text which supports our hypothesis (H1) thus. This contrast with similar state-of-the-art baselines supports the second key point (H2) by revealing the advantages of pre-training the Arabic language models using very big datasets. The narrowly designed AraBERT consistently surpasses models which are trained from the ground-up, which deeply expresses the valuable role of transfer learning in Arabic NLP tasks.

The results of this research also enable us to comprehend the challenges specifically associated with Arabic language processing. To handle the complexity of both high-degree Arabic and different dialects well, the transformer-based models use WordPiece tokenization and sub-word embeddings, among other things. This supports our hypothesis (H3), which posits that models specifically tailored to address Arabic-specific issues demonstrate enhanced performance. However, we must acknowledge that our analysis falls short in addressing some crucial aspects. We can only conduct the exploration on a specific number of datasets and metrics, but a wide variety of datasets and methodologies are available for selection.

Future studies could focus on a wider range of Arabic languages and explore the auto-generalization that arises from developing distinct models for various domains and dialects.

Furthermore, it will be necessary to examine whether simplicity is more important or performance because of this trade-off in H4. On the contrary, Transformer models with its potency of reaching higher accuracy have also the prices of more computational resources and training time compared to RNNs and CNNs. While balancing performance and efficiency is very important for the practical usage of Arabic language processing, that is how it works.

5.4. Limitations and Future Work

Despite the comprehensive scope of our comparative analysis, it's important to acknowledge some limitations. The initial phase of our study focuses on a few Arabic NLP tasks and datasets. However, these projects do not fully address all Arabic NLP needs; we anticipate further work to address these challenges effectively. Moreover, our study's datasets, while seemingly diverse and coherent, are limited, potentially failing to capture the fullness and diversity of the Arabic language. Future research could explore the generalization of deep learning models to larger scales and different types of datasets, encompassing domains beyond common domains, genres, and dialects. Moreover, we can characterize our investigation as model-centric; we gauge the model's accuracy using the F1-score and BLEU score. Although these indicators point to the model's strengths, they are unable to identify more subjective factors such as grace of form, sense, and correct consistency. To fully acknowledge the strengths and weaknesses of NLP models, further research must consider human evaluation as well as an analysis of the errors.

In addition to this, the recently emerged domain of deep learning provides soil for future studies. The new architectures, pre-training techniques, and transfer learning approaches are always in the race to go hand in hand with the developments, and choosing the ideal one for Arabic language processing remains a point of concern. The search for novel approaches that use state-of-the-art techniques such as graph neural networks and contrastive learning is worth pursuing, as this could stimulate more unique Arabic NLP engineering methodologies. In conclusion, the ethical implications of using Arabic language deep learning models should be considered researchers should concentrate on identifying areas of bias, transparency, and fairness in the models and corpuses utilized for Arabic NLP applications. Achieving models that are unbiased, interpretable, and contain ethical aspects should be the most critical approach for the responsible usage of the models in real-world application deployment environments.

6. CONCLUSIONS

This article presented a comparative study of deep approaches for Arabic language processing at an extreme level, highlighting two very promising ones. To find out how well three popular deep learning architectures—recurrent neural networks (RNNs), convolutional neural networks (CNNs), and transformers—did at five important Arabic natural language processing tasks, we looked at classification, dialect detection, techniques like sentiment analysis and named entity recognition, translation, and text classification. Our work proves that only transformer-based models, particularly the AraBERT, can systematically beat RNN and CNN models in tasks of all specificities. Pair t-tests validate the statistical superiority of

Transformers over their competitors across all metrics. This indicates that the Transformers' self-attention and pre-training using these large-scale Arabic corpora enable them to capture all the complex linguistic patterns and deliver state-of-the-art results in Arabic NLP.

This paper presented a large-scale English-Arabic comparative analysis that contributes to the Arabic NLP by proving the superiority of the transformer-based models, especially AraBERT, on a variety of tasks. As such, our work highlights the need to pre-train on large amounts of Arabic corpora and shows the value of transfer learning to boost the performance for downstream tasks in the field of NLP. In addition, the analysis we provide comparing and contrasting RNNs, CNNs, and Transformers provides practical insights on where each might excel or struggle with the complex Arabic language processing. These findings can help researchers and practitioners to choose the right architectures and settings depending on their Arabic NLP tasks and data.

This paper aims at two aspects. The first aspect is the main contribution, while the second is the focus. Initially, we proceed with a comprehensive analysis of deep learning architectures for a multitude of Arabic NLP tasks, in which the report includes the diathesis for these models and their limitations. Secondly, we present to you AraBERT, an exceptional Transformer-based model. The big speedup of Transformer-like models, especially Transformer in Arabic (AraBERT), could change many Arabic-language uses, like sentiment analysis for keeping an eye on social media, named entity recognition for getting information, and machine translation for talking to people who speak different languages. This approach utilizes text classification for content categorization, and dialect identification for speech recognition and text-to-speech systems. The ease of integration of elegant deep learning models developed for Arabic natural language processing will pave the way for better Arabic-specialist technologies with high accuracy and efficiency, thus making the understanding and use of Arabic content more accessible and convenient for users all over the world.

Along with this research, the direction for further investigations can take numerous forms. Among these avenues is the need to detail how we will adjust AraBERT and other Transformer models for tasks in the Arabic NLP space, such as legal text processing, healthcare data analyzation, and educational content generation. One other path is to research the combination of AraBERT with other techniques, for example, transfer learning and multi-task learning which will give the best performance and generalization across the tasks. In addition, more multifaceted and large-scale Arabic language resources, which include annotated corpora and benchmark, can provide higher platform deep learning model performance for plenty of Arabic NLP applications.

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