

# BERT-based Multi-Task Model for Country and Province Level Modern Standard Arabic and Dialectal Arabic Identification

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## Abstract

Dialect and standard language identification are crucial tasks for many Arabic natural language processing applications. In this paper, we present our deep learning-based system, submitted to the second NADI shared task for country-level and province-level identification of Modern Standard Arabic (MSA) and Dialectal Arabic (DA). The system is based on an end-to-end deep Multi-Task Learning (MTL) model to tackle both country-level and province-level MSA/DA identification. The latter MTL model consists of a shared Bidirectional Encoder Representation Transformers (BERT) encoder, two task-specific attention layers, and two classifiers. Our key idea is to leverage both the task-discriminative and the inter-task shared features for country and province MSA/DA identification. The obtained results show that our MTL model outperforms single-task models on most subtasks.

## 1 Introduction

The Arabic language is spoken by approximately 400 million people and characterized by different varieties. On the one hand, people of the Arab world tend to use Modern Standard Arabic (MSA) as a communication channel in formal situations (e.g. media, religion, education). On the other hand, Arabic dialects are usually used for informal communication in daily life. These dialects differ, to varying degrees, from one region to another.

Generally, existing research works categorized DA into four regions (Maghreb, Egypt, Gulf, and Levant) based on the coarse-grained taxonomy (Zaidan and Callison-Burch, 2014). Recently, several research studies classified DA into more fine-grained varieties such as country-level dialects (Salameh et al., 2018; Bouamor et al., 2019; Abdul-Mageed et al., 2020b).

In the last few years, Arabic dialect identification has gained much attention (Bouamor et al., 2019; El Mekki et al., 2020; Abdul-Mageed et al., 2020b,c). Identifying the dialect of an end-user is a very important task in many applications such as user profiling, personalized customer support, etc. Nevertheless, due to the nature and the structure of DA as well as MSA (Al-Sughaiyer and Al-Kharashi, 2004; Habash, 2010; Habash et al., 2012), this task faces several challenges.

Previous works on DA identification mainly focused on the use of traditional machine learning models (Abu Kwaik and Saad, 2019; Meftouh et al., 2019) and single-task deep learning models (Talafha et al., 2020). (El Mekki et al., 2020) introduced hierarchical models that perform the training and prediction of the country-level and province-level classification based on a sequential process. Recently, (Abdul-Mageed et al., 2020c) shown the effectiveness of MTL using MARBERT, a transformer-based language model pre-trained on a massive dataset of 128GB Arabic tweets, for both country-level and province-level DA identification.

In this paper, we tackle both the DA and MSA identification of the second NADI (Nuanced Arabic Dialect Identification) shared tasks: Country-level MSA identification, country-level DA identification, province-level MSA identification, and province-level DA identification (Abdul-Mageed et al., 2021). Our submitted system consists of an end-to-end deep MLT model that predicts both the province and the country of a given Arabic tweet. Our model leverages MARBERT’s contextualized word embedding (Abdul-Mageed et al., 2020a) with two task-specific attention layers that extract the task-discriminative features. The latter features are then concatenated with the encoder’s pooled embedding ([CLS] embedding) and are fed to the task classifiers. Thus, the core idea of our approach is to combine both task-discriminative and

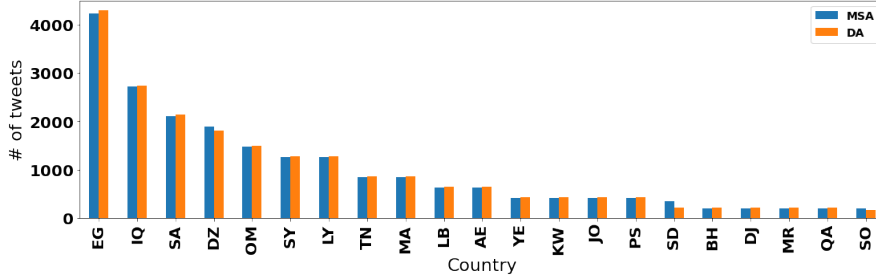


Figure 1: Label distribution of the training set for the country-level classification subtasks. Country code following the ISO 3166-1 alpha-2 (Wikipedia, 2020)

inter-task shared features for country and province MSA/DA identification. The obtained results show that our MTL model outperforms its single-task counterpart on all evaluated subtasks. These results prove the effectiveness of combining task-specific features and inter-task shared features for country-level and province-level MSA and DA identification.

The rest of this paper is organized as follows. Section 2 describes the NADI shared task’s datasets. Section 3 presents our proposed method. Section 4 summarizes the obtained results for both subtask 1 and subtask 2. In Section 5, we discuss these results. Finally, the conclusion is given in section 6.

## 2 Data

The second NADI shared task consists of four subtasks on MSA and DA country-level as well as province-level identification. Table 1 presents the four subtasks of NADI’2020.

Table 1: NADI’2021 DA and MSA identification subtasks

Data	Country-level	Province-level
MSA	Subtask 1.1	Subtask 2.1
DA	Subtask 1.2	Subtask 2.2

For both MSA and DA subtasks, the organizers of NADI’2021 provided a dataset of 31,000 labeled tweets covering 21 Arab countries and 100 Arab provinces. The training set consists of 21,000 tweets, while the rest 10,000 are equally distributed between the development and test sets. Finally, each tweet is assigned a single country label and a single province label. Figure 1 shows that the distribution of tweets for the country-level classification subtasks is unbalanced. Furthermore, Egypt, Iraq

and Saudi Arabia countries have the highest number of tweets, while Mauritania, Qatar and Somalia have the lowest one.

## 3 Method

Our multi-task model, for both tasks, consists of three main components: BERT encoder (MARBERT pre-trained language model), two task-specific attention layers, and two task classifiers.

### 3.1 BERT Encoder

The input tweets are encoded using a Bidirectional Encoder Representation from Transformers (BERT) model (Devlin et al., 2019). BERT employs multiple transformer blocks to encode the input text. This model is trained on large textual corpora by jointly optimizing the Masked Language Model (MLM) and the Next Sentence Prediction (NSP) objectives. Fine-tuning BERT model on the downstream tasks has shown state-of-the-art performances in many NLP applications.

In order to avoid domain shift, our end-to-end model for NADI’2021 uses MARBERT. In fact, MARBERT (Abdul-Mageed et al., 2020a) is a variation of BERT pre-trained on a large Arabic Twitter dataset (1 billion tweets) using only MLM objective (tweets are short).

### 3.2 Task-specific attention layer

Two task-specific attention layers are used to reward tokens’ hidden representation (contextual embedding) that contributes to the correct classification of tweets for the country-level and province-level tasks. These layers operate on top of the contextualized word embedding of the BERT encoder  $H = [h_1, h_2, \dots, h_n] \in \mathbb{R}^{n \times d}$ , where  $n$  is the sequence length and  $d$  is the embedding dimension. Hence, each task-specific attention layer (Bahdanau et al., 2015; Yang et al., 2016) can attend to some parts of the tweet to extract the task-

discriminative features. The attention mechanism is given by:

$$\begin{aligned} C &= \tanh(HW_a) \\ \alpha &= \text{softmax}(C^T W_\alpha) \\ v &= \alpha \cdot H^T \end{aligned}$$

where  $W_a \in \mathbb{R}^{d \times 1}$ ,  $W_\alpha \in \mathbb{R}^{n \times n}$  are the attention mechanism’s learnable parameters,  $C \in \mathbb{R}^{n \times 1}$  and  $\alpha \in [0, 1]^n$  weights the word hidden representations according to their relevance to the task,  $v$  represents the task-relevant information contained in a tweet.

### 3.3 Task classifier

The task classifier consists of one hidden layer and one output layer. The pooled output ( $h_{[CLS]}$  embedding) and the vector  $v$ , obtained using the task-specific attention layer, are concatenated and passed to the task classifier. The latter outputs the predicted task label.

### 3.4 Multi-task learning objective

Our MTL model is trained to jointly optimize both tasks’ cross-entropy losses. For the country-level MSA/DA identification, our model minimizes:

$$L_{Country}(\hat{y}^c, y^c) = - \sum_{i=1}^N \sum_{j=1}^l y_{ij}^c \log(\hat{y}_{ij}^c)$$

where  $y_{ij}^c$  is the ground-truth label,  $\hat{y}_{ij}^c$  is the predicted label,  $N$  is the number of training samples, and  $l$  is the number of countries ( $l = 21$ ).

For the province-level MSA/DA identification, our model is trained to minimize:

$$L_{Province}(\hat{y}^p, y^p) = - \sum_{i=1}^N \sum_{j=1}^k y_{ij}^p \log(\hat{y}_{ij}^p)$$

where  $y_{ij}^p$  is the ground-truth label,  $\hat{y}_{ij}^p$  is the predicted label, and  $k$  is the number of provinces ( $k = 100$ ).

Thus, the final loss of our model is:

$$L = L_{Country} + L_{Province}$$

Finally, our model is trained using Adam optimizer (Kingma and Ba, 2014), with a learning rate of  $1 \times 10^{-5}$ . Based on several experiments, the batch size and the number of epochs are set to 16 and 5, respectively. For tweets cleaning, we have implemented the same preprocessing pipeline that is used by MARBERT which consists of diacritics removal and mention substitution by USER token.

## 4 Results

In our experiments, we have investigated multiple models, starting from traditional machine learning techniques to transformer-based approaches. The obtained results show that MARBERT significantly outperforms the other approaches. For a fair comparison, our single-task model employs an attention layer over the contextualized word embedding of MARBERT and concatenates its outputs with the [CLS] token embedding for MSA and DA identification subtasks. It is worth mentioning that incorporating an attention layer into single-task and MTL models improves the results compared to performing the classification using only the [CLS] token embedding representation.

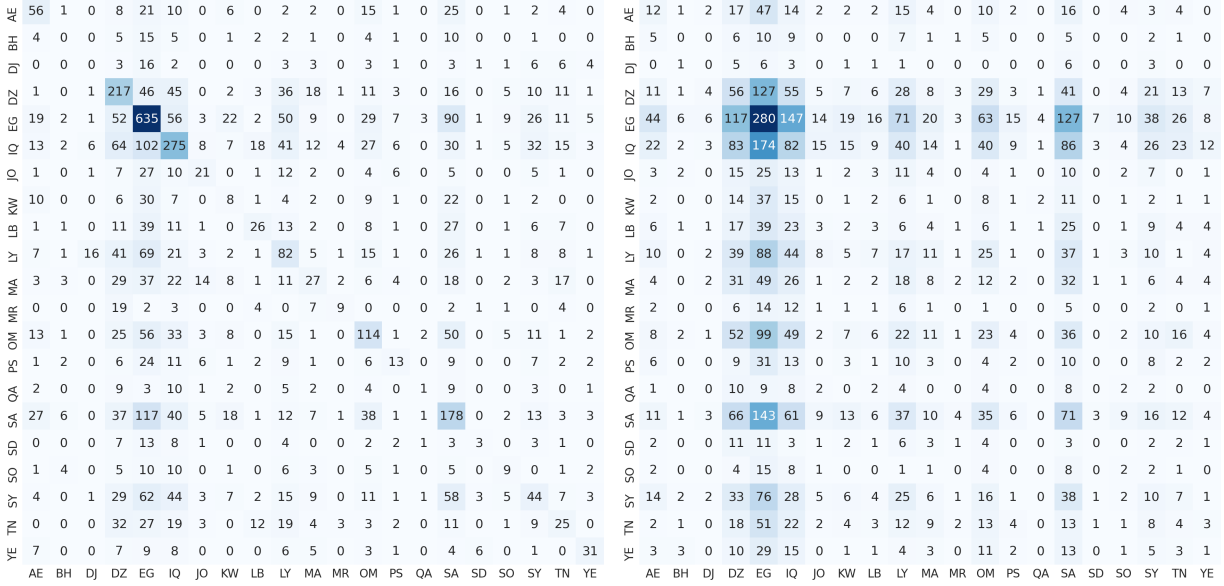
Table 2 presents the Macro-averaged F1-scores and the accuracies achieved using our evaluated single-task and MTL models on the four subtasks. The obtained results show that our attention-based multi-task model largely outperforms the single-task model on all subtasks’ Dev set and Test set. For MSA identification, at the country-level and province-level, our MTL model achieves F1-score performance increments of 1.49% and 0.35% respectively over the single-task model on the Dev set, while it achieves F1-score performance increments of 0.47% and 0.63% respectively over the single-task model for the Test set. For DA identification, at the country-level and province-level, the MTL model leads to F1-score performance increments of 0.42% and 0.42% over the single-task model, respectively on the Dev set, while it achieves increments of 1.57% and 2.02%, respectively on the Test set. This can be explained by the fact that our MTL model leverages signals from related tasks and boosts the performance of both. Moreover, through the task-specific attention layers, the MTL model extracts the task-discriminative features. Furthermore, employing task-specific features and global-shared features ([CLS] embedding) improves the performance of our MTL model.

## 5 Discussion

In order to analyze the results and explain the lower performance of our MTL model on some subtasks, Figure 2 draws the confusion matrices for DA and MSA identification at the country-level on the Dev set. The matrices highlight a number of strengths and weaknesses of our final model. On the one hand, the model performs well for countries with

	Dev/Test	Single-task model		Multi-task model	
		F1	Accuracy	F1	Accuracy
Subtask 1.1	Dev	21.56	34.35	<b>23.05</b>	<b>37.80</b>
	Test	20.90	33.73	<b>21.47</b>	<b>33.84</b>
Subtask 1.2	Dev	31.62	48.48	<b>32.04</b>	<b>51.28</b>
	Test	29.07	49.50	<b>30.64</b>	<b>50.30</b>
Subtask 2.1	Dev	6.05	6.63	<b>6.40</b>	<b>6.85</b>
	Test	4.72	5.00	<b>5.35</b>	<b>5.72</b>
Subtask 2.2	Dev	8.88	9.60	<b>9.40</b>	<b>9.84</b>
	Test	5.30	6.90	<b>7.32</b>	<b>7.92</b>

Table 2: Scores of our models (%) for the 4 subtasks (dev-sets and test-sets).



(a) MSA identification

(b) DA identification

Figure 2: The confusion matrices of our MTL model on the Dev set for country-level DA and MSA identification.

a high number of training examples such as Egypt, Algeria, and Iraq. On the other hand, the model shows poor performance in predicting true positives for countries with a low number of training examples, as it is the case of Djibouti and Bahrain. Moreover, the MSA country-level identification is a very challenging subtask since it is hard to find patterns to discriminate between countries and provinces based on standard language. Also, the model tends to make incorrect predictions for countries that are geographically close since their dialects have some minor differences (e.g. the Gulf countries) compared to other Arab countries.

## 6 Conclusion

In this paper, we introduced our submitted system to the second NADI shared task. We proposed an MTL model for joint country-level and province-

level identification of MSA and DA tweets. The model is based on the state-of-the-art MARBERT encoder and uses two task-specific attention layers to extract the task-discriminative features. The obtained results have shown that our MTL model outperforms the single-task model on all subtasks for both evaluation measures (Macro-F1 and accuracy).

Future research work will focus on developing task-interaction and class-interaction modules and mechanisms for coarse-grained and fine-grained DA and MSA identification.

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