NADI 2022:
The Third Nuanced Arabic Dialect Identification Shared Task
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Abstract

We describe the findings of the third Nuanced Arabic Dialect Identification Shared Task (NADI 2022). NADI aims at advancing state-of-the-art Arabic NLP, including Arabic dialects. It does so by affording diverse datasets and modeling opportunities in a standardized context where meaningful comparisons between models and approaches are possible. NADI 2022 targeted both dialect identification (Subtask 1) and dialectal sentiment analysis (Subtask 2) at the country level. A total of 41 unique teams registered for the shared task, of whom 21 teams have participated (with 105 valid submissions). Among these, 19 teams participated in Subtask 1, and 10 participated in Subtask 2. The winning team achieved $F_1=27.06$ on Subtask 1 and $F_1=75.16$ on Subtask 2, reflecting that both subtasks remain challenging and motivating future work in this area. We describe the methods employed by the participating teams and offer an outlook for NADI.

1 Introduction

Arabic is a collection of languages and language varieties some of which are not mutually intelligible, although it is sometimes conflated as a single language. Classical Arabic (CA) is the variety used in old Arabic poetry and the Qur’an, the Holy Book of Islam. CA continues to be used to date, side by side with other varieties, especially in religious and literary discourses. CA is also involved in code-switching contexts with Modern Standard Arabic (MSA) (Abdul-Mageed et al., 2020b). In contrast, as its name suggests, MSA is a more modern variety (Badawi, 1973) of Arabic. MSA is usually employed in pan-Arab media such as AlJazeera network and in government communication across the Arab world.¹ Dialectal Arabic (DA) is the term used to collectively refer to

¹https://www.aljazeera.com/

Figure 1: A map of the Arab World showing the 18 countries in the Subtask 1 dataset and the 10 countries in the Subtask 2 dataset. Each country is coded in a color different from neighboring countries. Subtask 2 countries are coded as circles with dark color.

Arabic dialects. DA is sometimes defined regionally into categories such as Gulf, Levantine, Nile Basin, and North African (Habash, 2010; Abdul-Mageed, 2015). More recent treatments of DA focus on more nuanced variation at the country or even sub-country levels (Bouamor et al., 2018; Abdul-Mageed et al., 2020b). Many of the works on Arabic dialects thus far have focused on dialect identification, the task of automatically detecting the source variety of a given text or speech segment.

In this paper, we introduce the findings and results of the third Nuanced Arabic Dialect Identification Shared Task (NADI 2022). NADI aims at encouraging research work on Arabic dialect processing by providing datasets and diverse modeling opportunities under a common evaluation setup. The first instance of the shared task, NADI 2020 (Abdul-Mageed et al., 2020a), focused on province-level dialects. NADI 2021 (Abdul-Mageed et al., 2021b), the second iteration of NADI, focused on distinguishing both MSA and DA according to their geographical origin at the country level. NADI 2022 extends on both editions and offers a richer context as it targets both Arabic dialect identification and dialectal sentiment analysis.

NADI 2022 shared tasks proposes two subtasks:
Subtask 1 on dialect identification, and Subtask 2 on dialect sentiment analysis. While we invited participation in either of the two subtasks, we encouraged teams to submit systems to both subtasks. By offering two subtasks, our hope was to receive systems that exploit diverse machine learning and other methods and architectures such as multi-task learning systems, ensemble methods, sequence-to-sequence architectures in single models such as the text-to-text Transformer, etc. Many of the submitted systems investigated diverse approaches, thus fulfilling our objective.

A total of 41 unique teams registered for NADI 2022. Of these, 21 unique teams actually made submissions to our leaderboard (n=105 valid submissions). We received 16 papers from 15 teams, of which we accepted 15 for publication. Results from participating teams show that both dialect identification at the country level and dialectal sentiment analysis from short sequences of text remain challenging even to complex neural methods. These findings clearly motivate future work on both tasks.

The rest of the paper is organized as follows: Section 2 provides a brief overview of Arabic dialect identification and sentiment analysis. We describe the two subtasks and NADI 2022 restrictions in Section 3. Section 4 introduces shared task datasets and evaluation setup. We present participating teams and shared task results and provide a high-level description of submitted systems in Section 5. We conclude in Section 6.

2 Literature Review

2.1 Arabic Dialects

Arabic can be categorized into CA, MSA, and DA. Although CA and MSA have been studied extensively (Harrell, 1962; Cowell, 1964; Badawi, 1973; Brustad, 2000; Holes, 2004), DA is has received more attention only in recent years. One major challenge for studying DA has been the lack of resources. For this reason, most pioneering DA works focused on creating resources, usually for only a small number of regions or countries (Gadalla et al., 1997; Diab et al., 2010; Al-Sabbagh and Girju, 2012; Sadat et al., 2014; Harrat et al., 2014; Jarrar et al., 2016; Khalifa et al., 2016; Al-Twairesh et al., 2018; El-Haj, 2020). A number of works introducing multi-dialectal datasets and regional level detection models followed (Zaidan and Callison-Burch, 2011; Elfardy et al., 2014; Bouamor et al., 2014; Meftouh et al., 2015).

Some of the earliest Arabic dialect identification shared tasks were offered as part of the VarDial workshop. These shared tasks used speech broadcast transcriptions (Malmasi et al., 2016), and later integrated acoustic features (Zampieri et al., 2017) and phonetic features (Zampieri et al., 2018) extracted from raw audio.

The Multi-Arabic Dialects Application and Resources (MADAR) project (Bouamor et al., 2018) was the first that introduced finer-grained dialectal data and a lexicon. The MADAR data was used for dialect identification at the country and city levels covering 25 cities in the Arab world (Salameh et al., 2018; Obeid et al., 2019). The MADAR data was commissioned rather than being naturally occurring, which might not be the best for dialect identification, especially when considering dialect identification in the social media context. Several larger datasets covering 10-21 countries were then introduced (Mubarak and Darwish, 2014; Abdul-Mageed et al., 2018; Zaghouani and Charfi, 2018; Abdelali et al., 2021; Issa et al., 2021; Baimukan et al., 2022). These datasets were mainly compiled from naturally-occurring posts on social media platforms such as Twitter. Some approaches for collecting dialectal data are unsupervised. A recent example is Althobaiti (2022) who describe an approach for automatically tagging Twitter posts with 15 country-level dialects and extracting relevant word lists. Some works also gather data at the fine-grained level of cities. For example, Abdul-Mageed et al. (2020b) introduced a Twitter dataset and a number of models to identify country, province, and city level variation in Arabic dialects. The NADI shared task (Abdul-Mageed et al., 2020a, 2021b) built on these efforts by providing datasets and common evaluation settings for identifying Arabic dialects. Althobaiti (2020) is a relatively recent survey of computational work on Arabic dialects.

2.2 Sentiment Analysis

Besides dialect identification, several studies investigate socio-pragmatic meaning (SM) exploiting Arabic data. SM refers to intended meaning in real-world communication and how utterances should be interpreted within the social context in which they are produced (Thomas, 2014; Zhang et al., 2022). Typical SM tasks include sentiment analysis (Abdul-Mageed et al., 2014; Abdul-Mageed, 2019), emotion recognition (Al-
NADI 2022 As introduced earlier, this current edition of NADI focuses on studying Arabic dialects at the country level as well as dialectal sentiment (i.e., sentiment analysis of data tagged with dialect labels). Our objective is that NADI 2022 can support exploring variation in social geographical regions that have not been studied before. We discuss NADI 2022 in more detail in the next section.

It is worth noting that NADI shared task datasets are starting to be used for various types of (e.g., linguistic) studies of Arabic dialects. For example, Alsudais et al. (2022) studies the effect of geographic proximity on Arabic dialects exploiting datasets from MADAR (Bouamor et al., 2018) and NADI (Abdul-Mageed et al., 2020a, 2021b).

3 Task Description

3.1 Shared Task Subtasks

The NADI 2022 shared task consists of two subtasks, both focused on dialectal Arabic at the country level. **Subtask 1** is about dialect identification and **Subtask 2** is about sentiment analysis of Arabic dialects. We now introduce each subtask.

Subtask 1 (Dialect Identification) The goal of Subtask 1 is to identify the specific country-level dialect of a given Arabic tweet. For this subtask, we reuse the training, development, and test datasets of 18 countries from NADI 2021 (Abdul-Mageed et al., 2021b). In addition to the test set of NADI 2021, we introduce a new test set manually annotated with \(k\) country-level dialects, where \(k = 10\) but is kept unknown to teams. We ask participants to submit system runs on these two test sets.

Subtask 2 (Dialectal Sentiment Analysis) The goal of Subtask 2 is to identify the sentiment of a given tweet written in Arabic. Tweets are collected from 10 different countries during the year of 2018 and involve both MSA and DA. The data are manually labeled with sentiment tags from the set \{positive, negative, neutral\}. More information about our data splits and evaluation settings for both Subtask 1 and Subtask 2 is given in Section 4.

Figure 1 shows the countries covered in NADI 2022 for both subtasks.
3.2 Shared Task Restrictions

We follow the same general approach to managing the shared task we adopted in NADI 2020 and NADI 2021. This includes providing participating teams with a set of restrictions that apply to all subtasks, and clear evaluation metrics. The purpose of our restrictions is to ensure fair comparisons and common experimental conditions. In addition, similar to NADI 2020 and 2021, our data release strategy and our evaluation setup through the CodaLab online platform facilitated competition management, enhanced timeliness of acquiring results upon system submission, and guaranteed ultimate transparency. Once a team registered in the shared task, we directly provided the registering member with the data via a private download link. We provided the data in the form of the actual tweets posted to the Twitter platform, rather than tweet IDs. This guaranteed comparison between systems exploiting identical data.

For both subtasks, we provided clear instructions requiring participants not to use any external data. That is, teams were required to only use the data we provided to develop their systems and no other datasets regardless how these are acquired. For example, we requested that teams do not search nor depend on any additional user-level information such as geolocation. To alleviate these strict constraints and encourage creative use of diverse (machine learning) methods in system development, we provided an unlabeled dataset of 10M tweets in the form of tweet IDs. This dataset is provided in addition to our labeled Train and Dev splits for the two subtasks. To facilitate acquisition of this unlabeled dataset, we also provided a simple script that can be used to collect the tweets. We encouraged participants to use the 10M unlabeled tweets in whatever way they wished.

4 Shared Task Datasets and Evaluation

**TWT-10** We collected \( \sim 10K \) tweets covering 10 Arab countries (Egypt, Iraq, Jordan, KSA, Kuwait, Oman, Palestine, Qatar, UAE, and Yemen) via the Twitter API. The tweets were collected during the year of 2018. We asked a total of three college-educated Arabic native speakers to annotate these tweets with three types of information: (1) dialectness (MSA vs. DA), (2) 10-way country-level dialects, and (3) three-way sentiment labels (i.e., \{positive, negative, neutral\}). For each of the 10 countries, 500 tweets were labeled by two different annotators. We calculated the inter-annotator agreement using Cohen’s Kappa. We obtained a Kappa (\( K \)) of 0.85 for the sentiment labeling task and \( K \) of 0.41 for the 10-way dialect identification one. Table 1 also presents the distribution of dialect and sentiment classes. It also shows that MSA comprises 50.86\% of TWT-10 (while DA is 49.14\%). Table 2 shows tweet examples with sentiment labels randomly selected from a number of countries representing different regions in our annotated dataset.

**Subtask 1 (Dialect Identification)** We use the dataset of Subtask 1.2 of NADI 2021 (i.e., country-level DA) (Abdul-Mageed et al., 2021b). This dataset was collected using tweets covering 21 Arab countries during a period of 10 months (Jan. to Oct.) during the year of 2019. It was heuristically labelled exploiting the users’ geo-location feature and mobility patterns and automatically cleaned to exclude non-Arabic and MSA tweets. For the purpose of this shared task, we keep the same training, development, and test splits as NADI 2021 but we exclude data from Djibouti, Somalia, and Mauritania since these are poorly represented in the dataset. We call the resulting dataset TWT-GEO. TWT-GEO includes 18 country-level dialects, split into Train (\( \sim 20K \) tweets), Dev (\( \sim 5K \) tweets), and Test-A (\( \sim 4.8K \) tweets). We refer to the test set of TWT-GEO as Test-A since we use an additional test split for evaluation, Test-B. Test-B contains 1.5K dialect tweets randomly sampled from the TWT-10 dataset described earlier.

| Country | Dialect | Sentiment | Total |
|---------|---------|-----------|-------|
|         | MSA     | DA        | Pos   | Neg   | Neut |       |
| Egypt   | 137     | 363       | 176   | 187   | 137  | 500   |
| Iraq    | 314     | 186       | 230   | 219   | 51   | 500   |
| Jordan  | 257     | 243       | 169   | 253   | 78   | 500   |
| KSA     | 300     | 200       | 194   | 152   | 154  | 500   |
| Kuwait  | 170     | 330       | 203   | 227   | 70   | 500   |
| Oman    | 340     | 160       | 166   | 179   | 155  | 500   |
| Palestine | 248  | 252       | 159   | 169   | 172  | 500   |
| Qatar   | 181     | 319       | 288   | 194   | 18   | 500   |
| UAE     | 270     | 230       | 232   | 112   | 156  | 500   |
| Yemen   | 326     | 174       | 118   | 198   | 184  | 500   |
| Total   | 2,543   | 2,457     | 1,935 | 1,890 | 1,175| 5,000 |

Table 1: The TWT-10 dataset class distributions.
**Table 2:** Randomly picked dialectal tweets from select countries in our annotated data for Subtask 2.

| Country | Train | Dev | Test-A | Test-B |
|---------|-------|-----|--------|--------|
| Algeria | 1,809 | 430 | 379    | ——     |
| Bahrain | 215   | 52  | 50     | ——     |
| Egypt   | 4,283 | 1,041 | 1,025 | 219    |
| Iraq    | 2,729 | 664 | 648    | 117    |
| Jordan  | 429   | 104 | 101    | 144    |
| KSA     | 2,140 | 520 | 501    | 116    |
| Kuwait  | 429   | 105 | 103    | 202    |
| Lebanon | 644   | 157 | 119    | ——     |
| Libya   | 1,286 | 314 | 309    | ——     |
| Morocco | 8,58  | 207 | 210    | ——     |
| Oman    | 1,501 | 355 | 360    | 91     |
| Palestine| 428 | 104 | 99     | 160    |
| Qatar   | 215   | 52  | 51     | 190    |
| Sudan   | 215   | 53  | 53     | ——     |
| Syria   | 1,287 | 278 | 279    | ——     |
| Tunisia | 859   | 173 | 211    | ——     |
| UAE     | 642   | 157 | 157    | 136    |
| Yemen   | 429   | 105 | 103    | 99     |

**Table 3:** Distribution of classes for Subtask 1 data.

**Subtask 2 (Sentiment Analysis)** For this subtask, we use the manually annotated 5,000 tweets (including both MSA and dialects) in TWT-10. We randomly split the tweets into **Train** (1,500 tweets), **Dev** (500 tweets), and **Test** (3,000 tweets). We intentionally provide a small training dataset to encourage various approaches (e.g., few-shot learning). Figure 2 shows the distribution of sentiment classes across the data splits.

**Unlabeled Dataset** We provide participants with a total of 10M unlabeled Arabic tweets in the form of tweet IDs. We refer to this collection as **UNLABELED-10M**. We collected these tweets in 2019. In UNLABELED-10M, Arabic was identified using Twitter language tag (ar). We included in our data package released to participants a simple script to collect these tweets. Participants were free to use UNLABELED-10M for any of the two subtasks.³

**Evaluation Metrics** The official evaluation metric for **Subtask 1** is Macro-Averaged $F_1$-score. We evaluate on Test-A and Test-B separately, and use the average score between these two test sets as the final score of Subtask 1. For **Subtask 2**, $F_{NP}$-score is the official metric, where we use the average of the $F_1$ scores of the **positive** and **negative** classes only while neglecting the neutral class. These metrics are obtained on blind test sets. We also report performance in terms of macro-averaged precision, macro-averaged recall and accuracy for systems submitted to each of the two subtasks.

Each participating team was allowed to submit...
up to five runs for each test set of a given subtask, and only the highest scoring run was kept for each team. Although official results are based only on a blind test set, we also asked participants to report their results on the Dev sets in their papers. We set up two CodaLab competitions for scoring participant systems. We plan to keep the Codalab competition for each subtask live post competition for researchers who would be interested in training models and evaluating their systems using the shared task blind test sets. For this reason, we will not release labels for the test sets of any of the subtasks.

5 Shared Task Teams & Results

5.1 Participating Teams

We received a total of 41 unique team registrations. After the testing phase, we received a total of 105 valid submissions from 21 unique teams. The breakdown across the subtasks is as follows: 42 submission for Test-A of Subtask 1 from 19 teams, 41 submissions for Test-B of Subtask 1 from 19 teams, 22 submissions for Subtask 2 from 10 teams. Table 4 lists the 21 teams. A total of 15 teams submitted a total of 16 description papers from which we accepted 15 papers for publication. Accepted papers are given in Table 4.

5.2 Baselines

We provide three baselines for each of the two subtasks. Baseline-I is based on the majority class in the Train data for each subtask. For Subtask 1, Baseline-I performs at $F_1=1.97$ on Test-A and $F_1=2.59$ on Test-B, hence it obtains an average $F_1$ of 2.28. For Subtask 2, Baseline-I performs at $F_{NP}=27.83$. Baseline-mBERT, Baseline-XLMR, and Baseline-MARBERT are fine-tuned multilingual BERT-Base model (mBERT) (Devlin et al., 2019), cross-lingual RoBERTa (XLMR) (Conneau and Lample, 2019), and MARBERT (Abdul-Mageed et al., 2021a), respectively. More specifically, we take checkpoints for these models from Hugginface Library (Wolf et al., 2020) and fine-tune each of them for 20 epochs with a learning rate of 2e-5 and batch size of 32. The maximum length of input sequence is set to 64 tokens. We evaluate each model at the end of each epoch and choose the best model based on performance on the respective Dev set. We then report performance of the best model on test sets. Baseline-MARBERT is our strongest baseline: it obtains $F_1=31.39$ on Test-A of Subtask 1, $F_1=16.94$ on Test-B of Subtask 1, average $F_1=24.17$ over Test-A and Test-B, and $F_{NP}=72.36$ on Subtask 2.

5.3 Shared Task Results

Table 5 presents the leaderboard of Subtask 1 and is sorted by the main metric of Subtask 1, i.e., average macro-$F_1$ score. As Tables 6 and 7 show, for each

![Table 4: List of teams that participated in either one or the two of subtasks. Teams with accepted papers are cited.](image-url)
team, we take their best score of Test-A and Test-B and then calculate the average macro-$F_1$ score over the best scores of these two test sets (i.e., Test-A and Test-B). Team rematchka (Abdel-Salam, 2022) obtained the best performance on Subtask 1 with 27.06 average macro-$F_1$. We can observe that seven teams outperform our strongest baseline, Baseline-MARBERT. Team rematchka also achieved the best $F_1$ of 36.48 on Test-A of Subtask 1.

Team UniManc (Khered et al., 2022) acquired the best $F_1$ of 18.95 on Test-B of Subtask 1. Results show that dialect identification based on text input is challenging. We note that there is a sizable discrepancy between test results on Test-A and Test-B: Test-B results are much lower. We believe the reason is that Test-B is derived from a different distribution (e.g., different collection time) as compared to training data of Subtask 1.

Table 8 shows the leaderboard of Subtask 2 and is sorted by the main metric of Subtask 2, $F_{NP}$ score. Again, Team rematchka achieved the best $F_{NP}$ score of 75.16. We observe that four and then eight teams outperformed our Baseline-MARBERT and Baseline-XLMR, respectively.
### Table 9: Summary of approaches used by participating teams who also submitted system descriptions. Teams are sorted by their performance on official metric, the average $\text{Macro-}F_1$ score over Test-A and Test-B for Subtask 1 and $F_1$ score over the positive and negative classes for Subtask 2. Classical machine learning (ML) refers to any non-neural machine learning methods such as naive Bayes and support vector machines. The term “neural nets” refers to any model based on neural networks (e.g., FFNN, RNN, and CNN) except Transformer models. Transformer refers to neural networks based on a Transformer architecture such as BERT. Data Aug.: Data Augmentation.

#### Subtask 1

| Team Name                | # submit | Main Metric | $\lambda$-gram | TF-IDF | Linguistic | Word embeds | Sampling | Classical ML | Neural nets | Transformer | Ensemble | Adapter | Multitask | Prompting | Distillation | Data Aug. | Pretraining |
|--------------------------|----------|-------------|-----------------|--------|------------|-------------|----------|--------------|-------------|-------------|----------|---------|----------|-----------|-------------|-----------|-------------|
| rematchka                | 6        | 27.06       | ✔               |        |            |             |          |              |             |             |          |         |          |           |             |           |             |
| UniManc                  | 6        | 26.86       |                 | ✔      |            |             |          |              |             |             |          |         |          |           |             |           |             |
| GOF                      | 4        | 26.44       |                 | ✔      |            |             |          |              |             |             |          |         |          |           |             |           |             |
| mtu_fiz                  | 8        | 25.50       |                 | ✔      |            |             |          |              |             |             |          |         |          |           |             |           |             |
| iCompass                 | 2        | 25.32       |                 | ✔      |            |             |          |              |             |             |          |         |          |           |             |           |             |
| ISL_AAST                 | 5        | 24.59       |                 | ✔      |            |             |          |              |             |             |          |         |          |           |             |           |             |
| Ahmed_and_Khalil         | 2        | 24.35       |                 | ✔      |            |             |          |              |             |             |          |         |          |           |             |           |             |
| Pythoneers               | 4        | 24.12       |                 | ✔      |            |             |          |              |             |             |          |         |          |           |             |           |             |
| Giyaseddin               | 3        | 22.42       |                 | ✔      |            |             |          |              |             |             |          |         |          |           |             |           |             |
| SQU                      | 4        | 22.42       |                 | ✔      |            |             |          |              |             |             |          |         |          |           |             |           |             |
| NLP_DI                   | 9        | 21.28       |                 | ✔      |            |             |          |              |             |             |          |         |          |           |             |           |             |
| RUTeam                   | 2        | 17.28       |                 | ✔      |            |             |          |              |             |             |          |         |          |           |             |           |             |
| 259                      | 2        | 16.89       |                 | ✔      |            |             |          |              |             |             |          |         |          |           |             |           |             |
| zTeam                    | 2        | 16.12       |                 | ✔      |            |             |          |              |             |             |          |         |          |           |             |           |             |
| XY                       | 10       | 15.80       |                 | ✔      |            |             |          |              |             |             |          |         |          |           |             |           |             |
| BFCAI                    | 6        | 15.48       |                 | ✔      |            |             |          |              |             |             |          |         |          |           |             |           |             |
| SUKI                     | 2        | 15.11       |                 | ✔      |            |             |          |              |             |             |          |         |          |           |             |           |             |

#### Subtask 2

| Team Name                | # submit | Main Metric | $\lambda$-gram | TF-IDF | Linguistic | Word embeds | Sampling | Classical ML | Neural nets | Transformer | Ensemble | Adapter | Multitask | Prompting | Distillation | Data Aug. | Pretraining |
|--------------------------|----------|-------------|-----------------|--------|------------|-------------|----------|--------------|-------------|-------------|----------|---------|----------|-----------|-------------|-----------|-------------|
| rematchka                | 4        | 75.16       |                 | ✔      |            |             |          |              |             |             |          |         |          |           |             |           |             |
| UniManc                  | 3        | 73.54       |                 | ✔      |            |             |          |              |             |             |          |         |          |           |             |           |             |
| BhamNLP                  | 3        | 73.46       |                 | ✔      |            |             |          |              |             |             |          |         |          |           |             |           |             |
| Pythoneers               | 1        | 73.40       |                 | ✔      |            |             |          |              |             |             |          |         |          |           |             |           |             |
| Ahmed_and_Khalil         | 1        | 71.46       |                 | ✔      |            |             |          |              |             |             |          |         |          |           |             |           |             |
| Giyaseddin               | 1        | 71.43       |                 | ✔      |            |             |          |              |             |             |          |         |          |           |             |           |             |
| ISL_AAST                 | 3        | 70.55       |                 | ✔      |            |             |          |              |             |             |          |         |          |           |             |           |             |
| ANLP-RG                  | 3        | 67.31       |                 | ✔      |            |             |          |              |             |             |          |         |          |           |             |           |             |
| RUTeam                   | 1        | 61.07       |                 | ✔      |            |             |          |              |             |             |          |         |          |           |             |           |             |

5.4 General Description of Submitted Systems

In Table 9, we provide a high-level summary of the submitted systems. For each team, we list their best score with the the main metric of each subtask and the number of their submissions. As shown in this table, most teams used Transformer-based pretrained language models, including mBERT (Devlin et al., 2019), ArabBERT (Antoun et al., 2020), MARBERT (Abdul-Mageed et al., 2021a).

The top team of Subtasks 1 and 2, i.e., rematchka, exploited MARBERT, AraBERT, and AraGPT2 (Antoun et al., 2021) with different prompting techniques and added linguistic features to their models.

The team placing first on Test-B of Subtask 1, i.e., UniManc, used MARBERT and enhanced the model on under-represented classes by introducing a sampling strategy.

Teams mtu_fiz (Shammary et al., 2022) and ISL_AAST used adapter modules to fine-tune MARBERT and applied data augmentation techniques.

Team UniManc found that further pre-training MARBERT on the 10M unlabelled tweets we released does not benefit Subtask 1 but improves performance on Subtask 2.

Six teams also utilized classical machine learning methods (e.g., SVM and Naive Bayes) to develop their systems.
6 Conclusion and Future Work

We presented the findings and results of the third Nuanced Arabic Dialect Identification shared task, NADI 2022. The shared task has two subtasks: Subtask 1 on country-level dialect identification (including 18 countries) and Subtask 2 on dialectal sentiment analysis (including 10 countries). NADI continues to be an attractive shared task, as reflected by the wide participation: 41 registered teams, 21 submitting teams scoring 105 valid models, and 15 published papers. Results obtained by the various teams show that both dialect identification and dialectal sentiment analysis of short text sequences remain challenging tasks. This motivates further work on Arabic dialects, and so we plan to run future iterations of NADI. Our experience from NADI 2022 shows that inclusion of additional subtasks, along with dialect identification, provides a rich context for modeling. Hence, we intend to continue adding at least one subtask (e.g., sentiment analysis covering more countries, emotion detection) to our main focus of dialect identification. We will also consider adding a data contribution track to NADI. In that track, teams may collect and label new datasets for public release.

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