NADI 2020: The First Nuanced Arabic Dialect Identification Shared Task

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Abstract

We present the results and findings of the First Nuanced Arabic Dialect Identification (NADI) Shared Task. This Task includes two subtasks: country-level dialect identification (Subtask 1) and province-level dialect identification (Subtask 2). The data for the shared task covers a total of 100 provinces from 21 Arab countries and are collected from the Twitter domain. As such, NADI is the first shared task to target naturally-occurring fine-grained dialectal text at the sub-country level. A total of 61 teams from 25 countries registered to participate in the tasks, thus reflecting the interest of the community in this area. We received 47 submissions for Subtask 1 from 18 teams and 9 submissions for Subtask 2 from 9 teams.

1 Introduction

The Arab world is an extensive geographical region across Africa and Asia, with a population of ~ 400 million people whose native tongue is Arabic. Arabic could be classified into three major types: (1) Classical Arabic (CA), the language of the Qur’an and early literature, (2) Modern Standard Arabic (MSA), the medium used in education and formal and pan-Arab media, and (3) dialectal Arabic (DA), a host of geographically and politically defined variants. Modern day Arabic is also usually described as a diglossic language with a so-called ‘High’ variety that is used in formal settings (MSA), and a ‘Low’ variety that is the medium of everyday communication (DA). The presumably ‘Low variety’ is in reality a collection of variants. One axis of variation for Arabic is geography where people from various sub-regions, countries, or even provinces within the same country, may be using language differently.

The goal of the First Nuanced Arabic Dialect Identification (NADI) Shared Task is to provide resources and encourage efforts to investigate questions focused on dialectal variation within the collection of Arabic variants. The NADI shared task targets 21 Arab countries and a total of 100 provinces across these countries. The shared task consists of two subtasks: country-level dialect identification (Subtask 1) and province-level detection (Subtask 2). We provide participants with a new Twitter labeled dataset that we collected exclusively for the purpose of the shared task. The dataset is publicly available for

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A total of 52 teams registered for the shard task, of whom 18 teams ended up submitting their systems for scoring. We then received 15 papers, of which we accepted 14.

This paper is organized as follows. We provide a brief overview of the computational linguistic literature on Arabic dialects in Section 2. We describe the two subtasks and dataset in Sections 3 and Section 4, respectively. And finally, we introduce participating teams, shared task results, and a high-level description of submitted systems in Section 5.

2 Related Work

As we explained in Section 1, Arabic could be viewed as comprised of 3 main types: CA, MSA, and DA. While CA and MSA have been studied and taught extensively, DA has only received more attention relatively recently (Harrell, 1962; Cowell, 1964; Badawi, 1973; Brustad, 2000; Holes, 2004).

A majority of DA computational efforts have targeted creating resources for country or regionally specific dialects (Gadalla et al., 1997; Diab et al., 2010; Al-Sabbagh and Girju, 2012; Sadat et al., 2014; Smaïli et al., 2014; Jarrar et al., 2016; Khalifa et al., 2016; Al-Twairesh et al., 2018; El-Haj, 2020). The expansion into multi-dialectal data sets and models to identify them was initially done at the regional level (Zaidan and Callison-Burch, 2011; Elfardy et al., 2014; Bouamor et al., 2014; Meftouh et al., 2015). A number of Arabic dialect identification shared tasks were organized as part of the VarDial workshop. These focused on regional varieties such as Egyptian, Gulf, Levantine, and North African based on speech broadcast transcriptions (Malmasi et al., 2016) but also acoustic features (Zampieri et al., 2017) and phonetic features (Zampieri et al., 2018) extracted from raw audio. Althobaiti (2020) presents a recent survey of computational work on Arabic dialects.

An early effort for creating finer grained parallel dialectal corpus and lexicon was done under the Multi Arabic Dialects Application and Resources (MADAR) project (Bouamor et al., 2018). The parallel data was created by commission under controlled settings to maximize its use for cross-dialectal comparisons and machine translation. Their data was also used for dialectal identification at the city level (Salameh et al., 2018; Obeid et al., 2019) of 25 Arab cities. One issue with the MADAR data in the context of identification is that it was commissioned and not naturally occurring. Concurrently, larger Twitter-based datasets covering 10-21 countries were also introduced (Mubarak and Darwish, 2014; Abdul-Mageed et al., 2018; Zaghouani and Charfi, 2018). Researchers are also starting to introduce DA datasets labeled for socio-pragmatics, e.g., (Abbes et al., 2020; Mubarak et al., 2020). The MADAR shared task (Bouamor et al., 2019) comprised two subtasks, one focusing on 21 Arab countries exploiting Twitter data manually labeled at the user level, and another on 25 Arab cities mentioned above. During the same time as NADI, Abdul-Mageed et al. (2020) describe data and models at country, province, and city levels.

The NADI shared task follows these pioneering works by availing data to the (Arabic) NLP community, and encouraging work on Arabic dialects. Similar to the MADAR shared task, we include a country-level dialect identification task (Subtask 1), and a sub-country dialect identification task (Subtask 2). However, our sub-country task is a province-level identification task with a much larger label set than MADAR’s city-level task, and is based on naturally occurring data. We hope that our work will be setting the stage for exploring variation in geographical regions that have not been studied before.

3 Task Description

The NADI shared task consists of two subtasks for country-level and province-level classification.

3.1 Subtask 1: Country-level Classification

The goal of Subtask 1 is to identify country-level dialects from short written sentences (tweets). NADI Subtask 1 is similar to previous works that have also taken country as their target (Mubarak and Darwish, 2014; Abdul-Mageed et al., 2018; Zaghouani and Charfi, 2018; Bouamor et al., 2019). Labeled data was provided to NADI participants with specific TRAIN and development (DEV) splits. Each of the 21 labels corresponding to the 21 countries is represented in both TRAIN and DEV. Teams could score their models through an online system on the DEV set before the deadline. Our TEST set of unlabeled
| Country Name | # of Provinces | # of Tweets | Train | Dev | Test | Total | %  |
|-------------|---------------|------------|------|-----|------|-------|----|
| Algeria     | 7             | 1,491      | 359  | 20  | 238  | 2,214 | 7.15|
| Bahrain     | 1             | 210        | 8    | 20  | 238  | 2,214 | 0.77|
| Djibouti    | 1             | 210        | 10   | 51  | 271  | 2,214 | 0.88|
| Egypt       | 21            | 4,473      | 1,070| 1,092| 6,635| 21.43 |
| Iraq        | 12            | 2,556      | 636  | 624 | 3,816| 12.33 |
| Jordan      | 2             | 426        | 104  | 102 | 634  | 2.05  |
| Kuwait      | 2             | 420        | 70   | 592 | 592  | 1.91  |
| Lebanon     | 3             | 639        | 110  | 5  | 705  | 2.35  |
| Libya       | 5             | 1,070      | 265  | 265 | 1,600| 5.17  |
| Mauritania  | 1             | 210        | 40   | 5 | 255  | 0.82  |
| Morocco     | 5             | 1,070      | 249  | 260 | 1,579| 5.10  |
| Oman        | 6             | 1,098      | 249  | 268 | 1,615| 5.22  |
| Palestine   | 2             | 420        | 102  | 102 | 624  | 2.02  |
| Qatar       | 2             | 234        | 104  | 61  | 399  | 1.29  |
| Saudi Arabia| 10            | 2,312      | 579  | 564 | 3,455| 11.16 |
| Somalia     | 1             | 210        | 51   | 312 | 312  | 1.01  |
| Sudan       | 1             | 210        | 51   | 312 | 312  | 1.01  |
| Syria       | 5             | 1,070      | 265  | 260 | 1,595| 5.15  |
| Tunisia     | 4             | 750        | 164  | 208 | 1,122| 3.62  |
| UAE         | 5             | 1,070      | 265  | 213 | 1,548| 5.00  |
| Yemen       | 4             | 851        | 206  | 179 | 1,236| 3.99  |
| **Total**   | **100**       | **21,000** | **4,957** | **5,000** | **30,957** | **100.00** |

Table 1: Distribution of country-level dialect identification data for Subtask 1 across our data splits.

tweets was released shortly before the system submission deadline. Participants were invited to submit their predictions to the online scoring system that housed the gold TEST set labels. We provide the distribution of the TRAIN, DEV, and TEST splits across countries in Table 1.

### 3.2 Subtask 2: Province-level Classification

The goal of Subtask 2 is to identify the specific state or province (henceforth, *province*) from a list of 100 provinces. The provinces are unequally distributed among the list of 21 countries. While efforts on city-level and country-level prediction were the topic of a previous shared task (Bouamor et al., 2019), to the best of our knowledge, the target of automatic dialect prediction at a small geographical region such as a province has not been previously investigated, thus lending novelty to this subtask. We acknowledge that this subtask has some affinity to work focused on predicting geolocation based on tweets. Nevertheless, geolocation prediction is performed at the level of users not tweets and hence is different. There are also differences between our work here and geolocation as to how the data was collected. We further explain this nuance in Section 4. The distribution of the classes across the 100 provinces in our data splits is presented in Table A1 in Appendix A.

For both Subtask 1 and Subtask 2, tweets in the TRAIN, DEV and TEST splits come from distinct sets of *users*, such that no user had their tweets in any two of the TRAIN, DEV, and TEST splits.

### 3.3 Restrictions and Evaluation Metrics

To ensure fair comparisons and common experimental conditions, we provided participating teams with a set of restrictions that apply to the two subtasks, and clear evaluation metrics. Our method of distributing the data as well as our evaluation setup through the CodaLab online platform also facilitated the competition management, enhanced timeliness of acquiring results upon system submission, and guaranteed ultimate transparency.²

We directly provided participants with the actual tweets posted to the Twitter platform, rather than tweet IDs. This enabled comparison between systems exploiting identical data. Since we shared actual tweets, we did not share tweet IDs with participants. This made it harder to collect data from the same user from which a tweet comes. For the two subtasks, we asked to only and exclusively use our distributed data. In other words, we provided instructions not to use any external data nor search or depend

²https://codalab.org/
| Country  | Province           | Tweet                                                                 |
|----------|--------------------|----------------------------------------------------------------------|
| Algeria  | Bordj-Bou-Arreridj | وانتم سيد الفاطمة ملائكة أكبر مصاصي منكم والرعبان دمرروا كل شيء جميع
|          |                    | الله المستعان                                                       |
|          | Jijel              | إبراهيم عليه السلام رحباً بالهجو |
| Egypt    | Asyut              | يا أعز أنت وأخوذ إبراهيم الذي زرع شعره واخذ الكلاkur عرف جاب الشعر منين في
|          |                    | جمعة وحده في رأس أنت نسيت نفسك ولا أرى المكان هو اللك من الشعار
|          | Suez               | بعد ما صالح سلم طرد زي الكلاkur نسيت أنت مرف حضرة علماء السما
|          |                    | غير المكان ورحش شيكوبيا المكان سجاد يا أجزهيداع _بام_ مرجي |
| KSA      | Ar-Riyad           | ﻓﻲ ﻚﺜر أﻣﻮر ﻋﻠﻰ ما ﺗﻌرﻔون ﺑ.TestTools١ ﻛﻪ ﺍﻧﻪ ﺑﻤﻼسﻹ وﻳﻠﻴﻨﻨﻴ ﻣﺮﺘﺎح ﻓﻌﻼ
|          |                    | ﻣﺴﺘﻘﻠﻴ ﻋﻨﺎ ﻋﻠﻰ ﻛﻤﺎ ﺗﻬﺒ تมง ﺑﺈن أولا ﺑﻤﻼسﻹ ﺑﺄد يأو ﺑأوأو ﻣﻨأوأو ﻣرصد
|          | Najran             | إنا ﻳﺤﺪ ﻣﻨأوأو ﺑأوأو ﻋن ﻣأوأو ﻤأوأو ﺑأوأو ﻋندأوأو ًأوأو ﺑأوأو ًأوأو ﺑأوأو
| Morocco  | Marrakech-Tensift-Al-Haouz | ﻳﺴﻌد ﻣأوأو ﻋن ﻋندأوأو ﻤأوأو ﻭأوأو ﻋندأوأو ﻤأوأو ﺑأوأو ًأوأو ﺑأوأو
|          | Tanger-Tetouan     | ﻯﺠا ﻓر ﻣأوأو ﻭأوأو ﻤأوأو ًأوأو ﺑأوأو ًأوأو ﺑأوأو ًأوأو ﺑأوأو ًأوأو ﺑأوأو
| Oman     | Muscat             | ﺑﺼرأ ﺑأر ﺑأر ﺑأر ﻣأوأو ﻭأوأو ﻤأوأو ًأوأو ﺑأوأو ًأوأو ﺑأوأو ًأوأو ﺑأوأو
|          | Ad-Dakhiliyah      | ﻳﺤد ﻣأوأو ﺑأوأو ﻤأوأو ًأوأو ﺑأوأو ًأوأو ﺑأوأو ًأوأو ﺑأوأو ًأوأو ﺑأوأو ًأوأو ﺑأوأو
| Sudan    | Khartoum           | ﻳﺤد ﻣأوأو ﺑأوأو ﻤأوأو ًأوأو ﺑأوأو ًأوأو ﺑأوأو ًأوأو ﺑأوأو ًأوأو ﺑأوأو ًأوأو ﺑأوأو
| UAE      | Abu-Dhabi          | ﻳﺤد ﻣأوأو ﺑأوأو ﻤأوأو ًأوأو ﺑأوأو ًأوأو ﺑأوأو ًأوأو ﺑأوأو ًأوأو ﺑأوأو ًأوأو ﺑأوأو
|          | Ras-Al-Khaymah     | ﻳﺤد ﻣأوأو ﺑأوأو ﻤأوأو ًأوأو ﺑأوأو ًأوأو ﺑأوأو ًأوأو ﺑأوأو ًأوأو ﺑأوأو ًأوأو 

Table 2: Randomly picked examples from select provinces and corresponding countries.

on any additional user-level information such as geolocation. In addition to our labeled TRAIN and DEV
splits, we provided tweet IDs for 10M tweets and a simple script that can be used to collect the tweets.
We did not provide any labels for this additional 10M tweet set, and encouraged participants to use it in
developing their models in any way they deemed useful.

For both subtasks, the official metric is macro-averaged $F_1$ score 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 subtask, and only the highest scoring run was kept as representing the team. Although
official results are based only on a blind TEST set, we also asked participants to report their results on
the DEV set in their papers. We setup two CodaLab competitions for scoring participant systems.3,4
We will keep the Codalab competition for each task live post competition, for researchers who would be
interested in training models and evaluating their systems using the shared task TEST set.

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3The CodaLab competition for Subtask 1 is accessible at: [https://competitions.codalab.org/competitions/24001.](https://competitions.codalab.org/competitions/24001)
4The CodaLab competition for Subtask 2 is accessible at: [https://competitions.codalab.org/competitions/24002.](https://competitions.codalab.org/competitions/24002)
4 Shared Task Datasets

We distributed a single dataset with two sets of labels, one for Subtask 1 and another for Subtask 2. In other words, the same tweet occurs in each of the two subtasks but with different subtask-specific labels. Additionally, we made available an unlabeled dataset for optional use in any of the two subtasks. We now provide more details about both the labeled and unlabeled data.

4.1 Data Collection

We used the Twitter API to crawl data from 100 provinces belonging to 21 Arab countries for 10 months (Jan. to Oct., 2019). Next, we identified users who consistently and exclusively tweeted from a single province during the whole 10 month period. We crawled up to 3,200 tweets from each of these users.

4.2 Data Sets

Subtask 1 and Subtask 2 Data We labeled tweets from each user with the country and province from which the user posted for the whole of the 10 months period, thus exploiting user consistent posting location as a proxy for dialect labels. Note that this labeling method can still have issues as we explain in Section 4.3. We randomly sampled 30,957 tweets of length 5 words or more from the collection and split them into TRAIN (n=21,000), DEV (n=4,957), and TEST (n=5,000). Although the task is at the tweet level, we sampled the data for each of the TRAIN, DEV, and TEST from a unique set of users (i.e., users are not shared across the 3 splits). We distribute data for the two subtasks directly to participants in the form of actual tweet text (i.e., hydrated content). Tables 1 and A1 show the distribution of tweets across the data splits for both Subtask 1 and Subtask 2, respectively.

Unlabeled 10M We also crawled 10 million posts from Arabic Twitter during 2019. We call this dataset UNLABELED 10M and distribute it in the form of tweet IDs along with a script that can be used to crawl the actual tweets. We put no restrictions on using UNLABELED 10M for system development for either of the two subtasks. Next, we discuss a number of nuances and issues found in the data.

4.3 Data Issues

Location as proxy for dialect. Our method of using consistent location (i.e., posting from the same location for at least 10 months) as a proxy for assigning dialect labels is useful, but not ideal. Even though this method allows us to collect provably relevant data, as manually verified in a small random sample of users (n=30), it can be error prone since a user with a dialect of one country can be posting from a different country during this whole period of 10 months.

MSA vs. Dialect. As we explained in Section 1, Arabic is usually characterized as a diaglossic language with MSA being the ‘High’ variety and DA as the ‘Low’ variety. Arabic users also switch between these two varieties. Most relevant to our work, communication in DA over social media is not devoid of MSA even at a level as short as that of a tweet. This can vary from one dialect to another, but also depending on a range of other factors including the user educational background, career, and the actual goal of the post itself. To illustrate, based on our intuition and occasional observation, users with training in language sciences (education), those in careers such as media or higher education (job), or those trying
to reach out to especially older generations or project religious or cultural authority (goal or pragmatic function) will likely use more MSA. Due to the co-existence of MSA and DA in the same tweet, we opted for using all the data we collected from the users for the competition. Alternatively, we could have identified MSA tweets either manually or automatically and removed these. We did not take that step in order to keep the task more challenging since a classifier would need to learn about patterns of MSA-DA mixing to perform well. A model would also need to acquire skills enabling it to tease apart tweets that may be overly or exclusively MSA. To explore the extent of MSA in the dataset, we run an in-house neural MSA-DA model (acc = 89.1%, F1 = 88.6%) on it. The model predicts the percentages of MSA data as follows: 49.5% for TRAIN, 46.6% for DEV, and 49.7% for TEST. This distribution needs to be couched with caution, however, since dialectal features can be subtle and mixed with MSA to varying degrees. Upon manual inspection of a random sample of tweets the model labeled as MSA, we identify examples that are fully and verifiably MSA such as #1 below. In addition, we observe sequences that carry dialectal features. For example #2 and #3 below have dialectal words (highlighted in orange):

1. محمد الله رب العالمين على نعمة الله لا تعد ولا تحصى ولا يغفل عن رزق كل خليه.
2. البيض الفاسد يندرد على بعضه يا صاحبي. قاتلهم الله.
3. ما أي أخذان مهتمين، أبادك، إنك تدقي عليكم.

We also observe that the more confident the MSA-DA model is (based on softmax value), the more likely its decision is correct. This suggests we can use a thresholding approach to filter out MSA tweets, should we desire to reduce MSA in the data. We leave further investigation of this issue to the future.

Non-Arabic Text. Despite efforts to exclusively keep Arabic content, our dataset had a small percentage (2.52%) of Farsi. While collecting the data, we only kept tweets assigned an Arabic language tag by the Twitter API. However, the API is error prone and hence some non-Arabic was not filtered out. To circumvent this, we only kept tweets that have at least three word written in Arabic script after running an internal normalizer that removes diacritics and reduced repetitions of consecutive characters of > 2 to only 2, replaced URLs and usernames with the generic strings URL and @USR. Even after this step, some Farsi leaked to our data. The reason is that Farsi is written in the same script as Arabic, with only a few differences. Aliwy et al. (2020) manually inspected the NADI TRAIN set and provided a distribution of Farsi tweets over the different countries. We share this distribution in Table 3.

| Country       | # tweet | # Farsi | % Farsi |
|---------------|---------|---------|---------|
| Algeria       | 1,491   | 5       | 0.34    |
| Egypt         | 4,473   | 2       | 0.04    |
| Iraq          | 2,556   | 382     | 14.95   |
| Morocco       | 1,070   | 1       | 0.09    |
| Oman          | 1,098   | 26      | 2.37    |
| Saudi Arabia  | 2,312   | 6       | 0.26    |
| Syria         | 1,070   | 3       | 0.28    |
| Tunisia       | 750     | 2       | 0.27    |
| UAE           | 1,070   | 7       | 0.65    |
| Yemen         | 851     | 70      | 8.23    |
| Total         | 21,000  | 504     | 2.40    |

Table 3: Distribution of tweets manually labeled as Farsi in TRAIN. We only provide countries with Farsi tweets, and remove the rest of 21 countries in NADI.
Table 4: List of the 14 teams that participated in Subtasks 1 and 2 and submitted description papers.

| Team                   | Affiliation                                      | Tasks |
|------------------------|--------------------------------------------------|-------|
| Mawdoo3 AI             | Mawdoo3 AI, Jordan                               | 1     |
| BERT_NGRAMS            | Mohammed VI Polytechnic University, Morocco      | 1,2   |
| ArabicProcessors       | Institut National de Statistique et d’Economie, Morocco | 1,2   |
| Tri-directional        | Faculty of Engineering, Alexandria University, Egypt | 1     |
| MMZ                    | Faculty of Engineering, Alexandria University, Egypt | 1     |
| QMUL Team              | Queen Mary University of London, United Kingdom | 1     |
| Code Lyoko             | Faculty of Engineering, Alexandria University, Egypt | 1     |
| TRY_NLP (Balaji and Bharathi, 2020) | SSN College of Engineering, India | 1,2   |
| Sorbonne (Ghoul and Lejeune, 2020) | Sorbonne Université, France | 1     |
| Speech Translation     | CRSTDLA Research Center, Algeria                 | 1     |
| LTG-ST (Touileb, 2020) | University of Oslo, Norway                       | 1     |
| Alexa (Bni Younes et al., 2020) | Jordan University of Science and Technology, Jordan | 1     |
| Alpha (AlShenaiti and Azmi, 2020) | King Saud University, Saudi Arabia                | 1     |
| IRAQ (Aliwy et al., 2020) | University of Kufa, Iraq                        | 1     |

Table 5: Results for Subtask 1. The numbers in parentheses are the ranks. The table is sorted on the $macro-F_1$ score, the official metric. Some teams did not submit description papers.

| Team                   | F1   | Accuracy | Precision | Recall  |
|------------------------|------|----------|-----------|---------|
| Mawdoo3 AI             | 26.78(1) | 42.86(1) | 32.52(1) | 25.19(1) |
| BERT_NGRAMS            | 25.99(2) | 39.66(2) | 30.26(2) | 24.85(2) |
| ArabicProcessors       | 23.26(3) | 38.34(3) | 27.17(4) | 22.43(5) |
| Tri-directional        | 23.09(4) | 37.70(5) | 26.40(5) | 23.04(4) |
| MMZ                    | 22.58(5) | 38.28(4) | 24.28(8) | 22.86(5) |
| QMUL Team              | 20.77(6) | 34.32(11)| 21.62(13)| 21.09(6) |
| Code Lyoko             | 20.34(7) | 36.26(8) | 27.83(3) | 20.56(8) |
| TRY_NLP                | 20.04(8) | 33.66(15)| 20.07(14)| 21.07(7) |
| Sorbonne               | 18.80(9) | 36.54(7) | 24.87(7) | 18.05(12)|
| Ikishaf                | 18.63(10)| 33.98(14)| 20.21(15)| 18.76(9) |
| Speech Translation     | 18.27(11)| 36.68(6) | 23.75(10)| 18.06(11)|
| LTG-ST                 | 17.71(12)| 36.22(9) | 24.93(6) | 17.21(13)|
| Alexa                  | 17.29(13)| 34.16(12)| 22.09(12)| 16.81(15)|
| NAYEL                  | 16.84(14)| 30.98(18)| 17.88(16)| 18.20(10)|
| DNLP                   | 16.50(15)| 31.28(17)| 17.84(17)| 17.04(14)|
| NLPRL                  | 15.77(16)| 35.06(10)| 23.96(9) | 15.92(16)|
| Alpha                  | 15.10(17)| 34.02(13)| 22.34(11)| 14.71(17)|
| Our Baseline II        | 13.32   | 32.38    | 14.57    | 16.97    |
| IRAQ                   | 12.45(18)| 31.60(16)| 16.39(18)| 12.67(18)|
| Our Baseline I         | 1.71    | 21.84    | 1.04     | 4.76     |

5.2 Participating Teams

We received a total of 61 unique team registrations, among which 7 teams registered to participate in Subtask 1 only, 1 team registered to participate in Subtask 2 only, and 53 teams registered to participate in both subtasks. After evaluation phase, we received 47 submissions for Subtask 1 from 18 teams and 9 submissions for subtask 2 from 4 teams. Of participating teams, a total of 15 teams submitted description papers all of which except one were accepted for publication. Table 5.2 lists the 14 teams whose papers were accepted.

5.3 Shared Task Results

Table 5 presents the best TEST results for all 18 teams who submitted systems for Subtask 1, regardless of whether they have submitted a paper. Based on the official metric, $macro-F_1$, Mawdoo3-AI obtained...
Table 6: Results for Subtask 2. The numbers in parentheses are the ranks. Table is sorted on the macro-$F_1$ score, the official metric. Team NAYEL does not have a description paper.

| Team                  | F1   | Accuracy | Precision | Recall  |
|-----------------------|------|----------|-----------|---------|
| BERT_NGRAMS           | 6.39 | 6.50     | 7.34      | 6.54    |
| Arabic Processors     | 5.75 | 6.80     | 6.78      | 6.74    |
| NAYEL                 | 4.99 | 5.22     | 5.52      | 5.17    |
| TRY_NLP               | 4.03 | 4.86     | 3.74      | 4.68    |
| Our Baseline II       | 2.13 | 3.32     | 4.04      | 3.22    |
| Our Baseline I        | 0.03 | 1.92     | 0.02      | 1.00    |

8 The full sets of results for Subtask 1 and Subtask 2 are in Tables A2 and A3, respectively, in Appendix A.

Table 7: Summary of approaches used by participating teams in Subtasks 1 and 2. Classical 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., RNN, CNN) except Transformer models. Transformer refers to neural networks based on a Transformer architecture such as BERT. The table is sorted by official metric, macro-$F_1$. We only list teams that submitted a description paper.

| Team               | # Submissions | $F_1$ | N-grams | TF-IDF | Word Embed. | Topic Models | Sampling | Classical ML | Neural Nets | Transformer | Ensemble | Hierarchical | Pre-Training | Data Augment. | Self-Training |
|--------------------|---------------|-------|---------|--------|-------------|--------------|----------|--------------|------------|-------------|----------|--------------|-------------|---------------|---------------|
| SUBTASK 1          |               |       |         |        |             |              |          |              |            |             |          |              |             |               |               |
| Mawdoo3 AI         | 3             | 26.78 | ✔️      | ✔️      | ✔️          | ✔️           | ✔️       | ✔️           | ✔️         | ✔️          | ✔️       | ✔️           | ✔️           | ✔️            | ✔️            |
| BERT_NGRAMS        | 4             | 25.99 | ✔️      | ✔️      | ✔️          | ✔️           | ✔️       | ✔️           | ✔️         | ✔️          | ✔️       | ✔️           | ✔️           | ✔️            | ✔️            |
| Arabic Processors  | 3             | 23.26 | ✔️      | ✔️      | ✔️          | ✔️           | ✔️       | ✔️           | ✔️         | ✔️          | ✔️       | ✔️           | ✔️           | ✔️            | ✔️            |
| Tri-directional    | 1             | 23.09 | ✔️      | ✔️      | ✔️          | ✔️           | ✔️       | ✔️           | ✔️         | ✔️          | ✔️       | ✔️           | ✔️           | ✔️            | ✔️            |
| MMZ                | 2             | 22.58 | ✔️      | ✔️      | ✔️          | ✔️           | ✔️       | ✔️           | ✔️         | ✔️          | ✔️       | ✔️           | ✔️           | ✔️            | ✔️            |
| QMUL Team          | 2             | 20.77 | ✔️      | ✔️      | ✔️          | ✔️           | ✔️       | ✔️           | ✔️         | ✔️          | ✔️       | ✔️           | ✔️           | ✔️            | ✔️            |
| Code Lyoko         | 2             | 20.34 | ✔️      | ✔️      | ✔️          | ✔️           | ✔️       | ✔️           | ✔️         | ✔️          | ✔️       | ✔️           | ✔️           | ✔️            | ✔️            |
| TRY_NLP            | 3             | 20.04 | ✔️      | ✔️      | ✔️          | ✔️           | ✔️       | ✔️           | ✔️         | ✔️          | ✔️       | ✔️           | ✔️           | ✔️            | ✔️            |
| Sorbonne           | 3             | 18.80 | ✔️      | ✔️      | ✔️          | ✔️           | ✔️       | ✔️           | ✔️         | ✔️          | ✔️       | ✔️           | ✔️           | ✔️            | ✔️            |
| Speech Translation | 3             | 18.27 | ✔️      | ✔️      | ✔️          | ✔️           | ✔️       | ✔️           | ✔️         | ✔️          | ✔️       | ✔️           | ✔️           | ✔️            | ✔️            |
| LTG-ST             | 2             | 17.71 | ✔️      | ✔️      | ✔️          | ✔️           | ✔️       | ✔️           | ✔️         | ✔️          | ✔️       | ✔️           | ✔️           | ✔️            | ✔️            |
| Alexa              | 3             | 17.29 | ✔️      | ✔️      | ✔️          | ✔️           | ✔️       | ✔️           | ✔️         | ✔️          | ✔️       | ✔️           | ✔️           | ✔️            | ✔️            |
| Alpha              | 5             | 15.10 | ✔️      | ✔️      | ✔️          | ✔️           | ✔️       | ✔️           | ✔️         | ✔️          | ✔️       | ✔️           | ✔️           | ✔️            | ✔️            |
| IRAQ               | 3             | 12.45 | ✔️      | ✔️      | ✔️          | ✔️           | ✔️       | ✔️           | ✔️         | ✔️          | ✔️       | ✔️           | ✔️           | ✔️            | ✔️            |
| SUBTASK 2          |               |       |         |        |             |              |          |              |            |             |          |              |             |               |               |
| BERT_NGRAMS        | 3             | 6.39  | ✔️      | ✔️      | ✔️          | ✔️           | ✔️       | ✔️           | ✔️         | ✔️          | ✔️       | ✔️           | ✔️           | ✔️            | ✔️            |
| Arabic Processors  | 1             | 5.75  | ✔️      | ✔️      | ✔️          | ✔️           | ✔️       | ✔️           | ✔️         | ✔️          | ✔️       | ✔️           | ✔️           | ✔️            | ✔️            |
| TRY_NLP            | 2             | 4.03  | ✔️      | ✔️      | ✔️          | ✔️           | ✔️       | ✔️           | ✔️         | ✔️          | ✔️       | ✔️           | ✔️           | ✔️            | ✔️            |

5.4 General Description of Submitted Systems

In Table 7, we provide a high-level description of the systems submitted to each subtask. For each team, we list the overall number of submissions per subtask, their overall best score, the features employed, the methods adopted/developed, and whether they have used the 10M unlabeled tweet dataset we provided to all teams. As can be seen from the table, the majority of the top teams have (1) used Transformers, (2) exploited the unlabeled data for further pre-training, and/or (3) have used self-training to enhance their models. The rest of participating teams have either used a type of neural networks other than Transformers or resorted to linear machine learning models, usually with some form of ensembling.
6 Conclusion and Future Work

We presented an overview of the NADI 2020 shared task. We described the dataset and identified areas of improvement especially related to its collection. We also provided a high-level description of participating teams. The number of submissions to the shared task reflects an interest in the community and calls for further work in the area of Arabic dialect detection, but also more generally Arabic dialect processing.

In the future, we plan to host a second iteration of the NADI shared task that will use new datasets and pursue a number of novel questions inspired by the issues discovered in this year’s task. For example, in addition to DA classification, we will propose MSA regional use classification as a subtask. Since MSA is shared across the Arab world, we hypothesize this will be a more challenging task than DA classification. We will also encourage teams to experiment with studying the interaction between MSA and DA in novel ways. For example, questions as to the utility of using DA data to improve MSA regional use classification systems and vice versa can be investigated exploiting various machine learning methods.

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Table A1: Distribution of the NADI data over provinces, by country, across our TRAIN, DEV, and TEST splits.
| Team Name          | F1    | Accuracy | Precision | Recall  |
|--------------------|-------|----------|-----------|---------|
| Mawdoo3 AI         | 26.75 | 42.86    | 32.52     | 25.19   |
| Arabic Processors  | 26.75 | 42.56    | 31.51     | 25.19   |
| BERT_NGRAMS        | 26.75 | 43.18    | 31.59     | 25.19   |
| Arabic Processors  | 26.75 | 37.70    | 26.49     | 22.04   |
| Mawdoo3 AI         | 26.75 | 38.42    | 27.40     | 22.40   |
| Arabic Processors  | 26.75 | 38.28    | 26.70     | 22.12   |
| Mawdoo3 AI         | 26.75 | 38.56    | 27.83     | 22.12   |
| Arabic Processors  | 26.75 | 38.34    | 27.17     | 22.43   |
| Arabic Processors  | 26.75 | 37.70    | 26.40     | 22.04   |
| Mawdoo3 AI         | 26.75 | 38.28    | 26.70     | 22.12   |
| Arabic Processors  | 26.75 | 38.34    | 27.17     | 22.43   |
| Arabic Processors  | 26.75 | 37.70    | 26.40     | 22.04   |
| Arabic Processors  | 26.75 | 38.28    | 26.70     | 22.12   |
| Arabic Processors  | 26.75 | 38.34    | 27.17     | 22.43   |
| Arabic Processors  | 26.75 | 37.70    | 26.40     | 22.04   |
| Arabic Processors  | 26.75 | 38.28    | 26.70     | 22.12   |
| Arabic Processors  | 26.75 | 38.34    | 27.17     | 22.43   |
| Arabic Processors  | 26.75 | 37.70    | 26.40     | 22.04   |
| Arabic Processors  | 26.75 | 38.28    | 26.70     | 22.12   |
| Arabic Processors  | 26.75 | 38.34    | 27.17     | 22.43   |
| Arabic Processors  | 26.75 | 37.70    | 26.40     | 22.04   |
| Arabic Processors  | 26.75 | 38.28    | 26.70     | 22.12   |
| Arabic Processors  | 26.75 | 38.34    | 27.17     | 22.43   |
| Arabic Processors  | 26.75 | 37.70    | 26.40     | 22.04   |
| Arabic Processors  | 26.75 | 38.28    | 26.70     | 22.12   |
| Arabic Processors  | 26.75 | 38.34    | 27.17     | 22.43   |
| Arabic Processors  | 26.75 | 37.70    | 26.40     | 22.04   |
| Arabic Processors  | 26.75 | 38.28    | 26.70     | 22.12   |
| Arabic Processors  | 26.75 | 38.34    | 27.17     | 22.43   |
| Arabic Processors  | 26.75 | 37.70    | 26.40     | 22.04   |
| Arabic Processors  | 26.75 | 38.28    | 26.70     | 22.12   |
| Arabic Processors  | 26.75 | 38.34    | 27.17     | 22.43   |
| Arabic Processors  | 26.75 | 37.70    | 26.40     | 22.04   |
| Arabic Processors  | 26.75 | 38.28    | 26.70     | 22.12   |
| Arabic Processors  | 26.75 | 38.34    | 27.17     | 22.43   |
| Arabic Processors  | 26.75 | 37.70    | 26.40     | 22.04   |
| Arabic Processors  | 26.75 | 38.28    | 26.70     | 22.12   |
| Arabic Processors  | 26.75 | 38.34    | 27.17     | 22.43   |
| Arabic Processors  | 26.75 | 37.70    | 26.40     | 22.04   |
| Arabic Processors  | 26.75 | 38.28    | 26.70     | 22.12   |
| Arabic Processors  | 26.75 | 38.34    | 27.17     | 22.43   |
| Arabic Processors  | 26.75 | 37.70    | 26.40     | 22.04   |
| Arabic Processors  | 26.75 | 38.28    | 26.70     | 22.12   |
| Arabic Processors  | 26.75 | 38.34    | 27.17     | 22.43   |
| Arabic Processors  | 26.75 | 37.70    | 26.40     | 22.04   |
| Arabic Processors  | 26.75 | 38.28    | 26.70     | 22.12   |
| Arabic Processors  | 26.75 | 38.34    | 27.17     | 22.43   |
| Arabic Processors  | 26.75 | 37.70    | 26.40     | 22.04   |
| Arabic Processors  | 26.75 | 38.28    | 26.70     | 22.12   |
| Arabic Processors  | 26.75 | 38.34    | 27.17     | 22.43   |
| Arabic Processors  | 26.75 | 37.70    | 26.40     | 22.04   |
| Arabic Processors  | 26.75 | 38.28    | 26.70     | 22.12   |
| Arabic Processors  | 26.75 | 38.34    | 27.17     | 22.43   |
| Arabic Processors  | 26.75 | 37.70    | 26.40     | 22.04   |
| Arabic Processors  | 26.75 | 38.28    | 26.70     | 22.12   |
| Arabic Processors  | 26.75 | 38.34    | 27.17     | 22.43   |
| Arabic Processors  | 26.75 | 37.70    | 26.40     | 22.04   |
| Arabic Processors  | 26.75 | 38.28    | 26.70     | 22.12   |
| Arabic Processors  | 26.75 | 38.34    | 27.17     | 22.43   |
| Arabic Processors  | 26.75 | 37.70    | 26.40     | 22.04   |
| Arabic Processors  | 26.75 | 38.28    | 26.70     | 22.12   |
| Arabic Processors  | 26.75 | 38.34    | 27.17     | 22.43   |

Table A2: Full results for Subtask 1. The numbers in parentheses are the ranks. The table is sorted on the macro $F_1$ score, the official metric.

| Team Name          | F1    | Accuracy | Precision | Recall  |
|--------------------|-------|----------|-----------|---------|
| BERT_NGRAMS        | 6.39  | 6.50     | 7.84      | 6.54    |
| Arabic Processors  | 6.08  | 6.16     | 7.78      | 6.03    |
| NAYEL              | 5.75  | 6.80     | 6.78      | 6.47    |
| BERT_NGRAMS        | 5.42  | 5.32     | 5.00      | 5.24    |
| Alpha              | 4.99  | 5.22     | 5.25      | 5.17    |
| Alpha              | 4.61  | 5.24     | 4.34      | 4.69    |
| Alpha              | 4.03  | 4.86     | 3.74      | 4.08    |
| Alpha              | 3.94  | 4.54     | 3.86      | 4.45    |
| Alpha              | 3.60  | 3.84     | 3.83      | 3.85    |

Table A3: Full results for Subtask 2. The numbers in parentheses are the ranks. The table is sorted on the macro $F_1$ score, the official metric.