WojoodNER 2024: The Second Arabic Named Entity Recognition Shared Task

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Abstract

We present WojoodNER-2024, the second Arabic Named Entity Recognition (NER) Shared Task. In WojoodNER-2024, we focus on fine-grained Arabic NER. We provided participants with a new Arabic fine-grained NER dataset called $Wojood_{Fine}$, annotated with subtypes of entities. WojoodNER-2024 encompassed three subtasks: (i) Closed-Track Flat Fine-Grained NER, (ii) Closed-Track Nested Fine-Grained NER, and (iii) an Open-Track NER for the Israeli War on Gaza. A total of 43 unique teams registered for this shared task. Five teams participated in the Flat Fine-Grained Subtask, among which two teams tackled the Nested Fine-Grained Subtask and one team participated in the Open-Track NER Subtask. The winning teams achieved F_1 scores of 91% and 92% in the Flat Fine-Grained and Nested Fine-Grained Subtasks, respectively. The sole team in the Open-Track Subtask achieved an F_1 score of 73.7%.

1 Introduction

NER plays a crucial role in various Natural Language Processing (NLP) applications, such as question-answering systems (Shaheen and Ezzeldin, 2014), knowledge graphs (James, 1991), and semantic search (Guha et al., 2003), information extraction and retrieval (Jiang et al., 2016), word sense disambiguation (Jarrar et al., 2023b; Al-Hajj and Jarrar, 2021), machine translation (Jain et al., 2019; Khurana et al., 2022), automatic summarization (Summerscales et al., 2011; Khurana et al., 2022), interoperability (Jarrar et al., 2021) and cybersecurity (Tikhomirov et al., 2020).

NER involves identifying mentions of named entities in unstructured text and categorizing them into predefined classes, such as PERS, ORG, GPE, LOC, EVENT, and DATE. Given the relative scarcity of resources for Arabic NLP, research in Arabic NER has predominantly concentrated on "flat" entities



Figure 1: Visualization of the fine-grained entity types in $Wojood_{Fine}$

and has been limited to a few "coarse-grained" entity types, namely PERS, ORG, and LOC. To address this limitation, the WojoodNER shared task series was initiated (Jarrar et al., 2023a). It aims to enrich Arabic NER research by introducing Wojood and $Wojood_{Fine}$ (Liqreina et al., 2023), nested and fine-grained Arabic NER corpora.

In WojoodNER-2024 we provide a new version of Wojood, called $Wojood_{Fine}$. $Wojood_{Fine}$ enhances the original Wojood corpus by offering fine-grained entity types that are more granular than the data provided in WojoodNER-2023. For instance, GPE is now divided into seven subtypes: COUNTRY, STATE-OR-PROVINCE, TOWN, NEIGHBORHOOD, CAMP, GPE_ORG, and SPORT. LOC, ORG, and FAC are also divided into subtypes as shown in Figure 1. $Wojood_{Fine}$ contains approximately 550k tokens and annotated with 51 entity types and subtypes, covering 47k subtype entity mentions. It is worth mentioning that SinaTools supports Wojood

and can be accessed via Application Programming Interface (API) (Hammouda et al., 2024).

Teams were invited to experiment with various approaches, ranging from classical machine learning to advanced deep learning and transformerbased techniques, among others. The shared task generated a remarkably diverse array of submissions. A total of 43 teams registered to participate in the shared task. Among these, five teams successfully submitted their models for evaluation on the blind test set during the final evaluation phase.

The rest of the paper is organized as follows: Section 2 provides a brief overview of Arabic NER. We describe the three subtasks and the shared task restrictions in Section 3. Section 4 introduces shared task datasets and evaluation. We present the participating teams, submitted systems and shared task results in Section 5. We conclude in Section 6.

2 Literature Review

NER has been an area of active research for many years, witnessing notable progress recently. This section will cover the evolution from initial efforts in recognizing flat-named entities to the current focus on nested NER, with a particular emphasis on Arabic NER, including discussions on corpora, methodologies, and shared tasks.

Corpora. The majority of Arabic NER corpora are designed for flat NER annotation. ANER-Corp (Benajiba et al., 2007), derived from news sources, contains approximately 150k tokens and focuses on four specific entity types. CANER-Corpus (Salah and Zakaria, 2018) targets Classical Arabic (CA) and includes a dataset of 258ktokens annotated for 14 types of entities related to religious contexts. The ACE2005 (Walker et al., 2005) corpus is multilingual and includes Arabic texts annotated with five distinct entity types. The Ontonotes5 (Weischedel et al., 2013) dataset features around 300k tokens annotated with 18 different entity types. However, these corpora are somewhat dated and primarily cover media and political domains, which may not accurately reflect contemporary Arabic usage, particularly as language models are sensitive to changes over time and across domains. Recently, (Jarrar et al., 2022) introduced Wojood, the largest Arabic NER corpus to date, notable for supporting both flat and nested entity annotations. This corpus, essential for this shared task, includes about 550k tokens and covers 21 unique entity types across Modern Standard Arabic (MSA) and two Arabic dialects (Palestinian Curras2 and Lebanese Baladi corpora (Haff et al., 2022)). *Wojood*_{Fine} (Liqreina et al., 2023), an extension of Wojood adds support for entity sub-types, with a total of 51 entities organized in two-level hierarchy. It is important to note that Wojood has been recently extended to include relationships (Aljabari et al., 2024).

Methodologies. Research in Arabic NER employs a variety of approaches, ranging from rulebased systems (Shaalan and Raza, 2007; Jaber and Zaraket, 2017) to machine learning techniques (Settles, 2004; Abdul-Hamid and Darwish, 2010; Zirikly and Diab, 2014; Dahan et al., 2015; Darwish et al., 2021). Recent studies have adopted deep learning strategies, utilizing character and word embeddings in conjunction with Long-Short Term Memory (LSTM) (Ali et al., 2018), and BiL-STM architectures paired with Conditional Random Field (CRF) layer (El Bazi and Laachfoubi, 2019; Khalifa and Shaalan, 2019). Deep Neural Networks (DNN) are explored in (Gridach, 2018), alongside pretrained Language Models (LM) (Jarrar et al., 2022; Liqreina et al., 2023). Wang et al. (2022) conducted a comprehensive review of various approaches to nested entity recognition, including rule-based, layered-based, region-based, hypergraph-based, and transition-based methods. Fei et al. (2020) introduced a multi-task learning framework for nested NER using a dispatched attention mechanism. Ouchi et al. (2020) developed a method for nested NER that calculates all region representations from the contextual encoding sequence and assigns a category label to each. Readers can also refer to the WojoodNER-2023 shared task for DNN techniques used for flat and nested ArabicNER (Jarrar et al., 2023a).

Shared tasks. While numerous shared tasks exist for NER across different languages and domains, such as MultiCoNER for multilingual complex NER (Malmasi et al., 2022) the HIPE-2022 for NER and linking in multilingual historical documents (Ehrmann et al., 2022), RuNNE-2022 for nested NER in Russian (Artemova et al., 2022), and NLPCC2022 for entity extraction in the material science domain (Cai et al., 2022). WojoodNER-2023 for flat and nested Arabic NER (Jarrar et al., 2023a), upon which WojoodNER-2024 builds on to offer support for entity sub-

types.

There are several related shared tasks for understanding Arabic MSA and dialects, such as the ArabicNLU for word-sense disambiguation (Khalilia et al., 2024; Jarrar et al., 2023b), NADI for dialect identification (Abdul-Mageed et al., 2023), AraFinNLP for Cross-dialect Intent detection (Malaysha et al., 2024), among others.

3 Task Description

WojoodNER-2024 confronts the intricacies of Arabic NER with three distinct subtasks: Flat Fine-Grained NER, Nested Fine-Grained NER, and Open-Track NER. These subtasks provide an evaluation environment, allowing researchers to experiment with diverse approaches for identifying and classifying named entities, along with their subtypes, under controlled (closed) and flexible (open) settings.

Remark: the Wojood dataset used in WojoodNER-2023 (Jarrar et al., 2023a) cannot be used in this Shared Task because the two datasets follow different annotation guidelines.

3.1 Closed-Track Flat Fine-Grained NER

In this subtask, we provide the $Wojood_{Fine}$ Flat train (70%) and development (10%) datasets. The final evaluation of the submitted contributions from participants is conducted on the test set (20%). The flat NER dataset follows the same split as the nested NER dataset. The key difference in flat NER is that each token is assigned a single tag, corresponding to the first high-level tag assigned in the nested NER dataset, and followed by a single tag in the second level (subtype). This subtask is a closed track, thus participants can only use the provided datasets to train their systems, with no external datasets permitted.

3.2 Closed-Track Nested Fine-Grained NER

This subtask is similar to Subtask 1. We provide the Wojood-Fine Nested train (70%) and development (10%) datasets, with the final evaluation conducted on the test set (20%). This subtask is a closed track, which means participants can only use the provided datasets to train their systems.

3.3 Open-Track NER - Israeli War on Gaza

This subtask aims to enable participants to explore the benefits of NER in real-world scenarios. Participants can use external resources and are encouraged to experiment with generative models in various ways, such as fine-tuning, zero-shot learning, and in-context learning. The emphasis on generative models in this subtask is intended to help the Arabic NLP research community gain a better understanding of the capabilities and performance gaps of Large Language Models (LLMs) in information extraction, which is currently a less explored area.

We have curated NER dataset called Wojood^{Gaza} pertaining to the ongoing Israeli War on Gaza, based on the assumption that discourse about recent global events will involve mentions from different data distributions. For this subtask, we have collected data from five news domains related to the War, while keeping the identities of these domains confidential. Participants have been provided with a development dataset (10k tokens, 2k from each of the five domains) and a testing dataset (50k tokens, 10k from each domain). Both datasets have been manually annotated with fine-grained named entities, following the same annotation guidelines as in Subtask 1 and Subtask 2, as outlined in (Liqreina et al., 2023). This subtask is divided into two subtasks: 3A-flat and 3B-nested.

3.4 Restrictions

This section outlines the guidelines for participating in the WojoodNER-2024 Shared Task. These rules have been put in place to ensure fairness and transparency for all participants. They also aim to uphold the credibility of the task's assessment process, which is further elaborated on the official shared task FAQ page.

External data. For Subtask 1 and 2, participants are strictly forbidden from using external data from previously labeled datasets or employing taggers previously trained to predict named entities. The use of any resources with prior knowledge of NER is not permitted. On the contrary, Subtask 3 allows the use external resources.

Data format constraints. Submissions for the task must be in a single file containing the model's predictions in CoNLL format. This format includes multiple space-separated columns: the first column for tokens and the subsequent columns for tags. For both flat and nested NER, the tag columns follow a predefined order specified on the shared task webpage. The IOB2 scheme (Sang and Veenstra, 1999) is used for submissions, consis-

tent with the Wojood dataset. Additionally, text segments are separated by a blank line.

4 Datasets and Evaluation Metrics

In this section, we will describe the dataset, evaluation metrics, and the submission procedure.

Datasets The WojoodNER-2024 shared task utilizes the $Wojood_{Fine}$ corpus as a dataset for Subtasks 1 and 2 (Ligreina et al., 2023). For Subtask 3, a different dataset called Wojood^{Gaza} is utilized that is related to the War on Gaza. The $Wojood_{Fine}$ corpus comprises approximately 550k tokens, annotated with nest named entities, using 51 entity types. For the purposes of the shared task, we created a flat NER dataset based on the nest NER dataset. That is, the flat NER dataset is created by simplifying the nested NER and reducing subtypes to the top level only as illustrated in Figure 2 and 3. For both Subtask 1 and Subtask 2, we partitioned the data at the domain level into training, development, and test datasets with a split of 70:10:20, respectively.

Table 1 presents the details of the datasets used in Subtask 1 (FlatNER) and Subtask 2 (NestNER).



Figure 2: Flat NER example.



Figure 3: Nested NER example.

The dataset for Subtask 3 is called *Wojood^{Gaza}*. It includes 60k tokens that we collected and annotated specifically for this shared task. The corpus was collected from online news articles published at these outlets: Institute for Palestine Studies, World Health Organization, Palestinian Ministry of Health, Palestine Monetary Authority, Aljazeera, Palestine Economy Portal, Wafa, BNews, AlAraby, Law for Palestine, United Nations, CNN

Business, Al Arabiya, Sky News, CNBC Arabia, RT Arabic, Euro News, BBC Arabic.

The articles that were collected from the period of January-March 2024, covering one of these five domains (politics, law, economy, finance, health) and were directly related to the War on Gaza. For each domain, we collected about 12k tokens. Participants are provided with the development dataset (10k tokens, 2k from each of the five domains), and a testing dataset (50k tokens, 10k from each domain). Domain names are not provided to the participants. *Wojood*^{Gaza} was annotated following the same guidelines as *Wojood*_{Fine} (Ligreina et al., 2023).

Evaluation metrics. The official and primary evaluation metric for Subtask 1, Subtask 2, and Subtask 3 is the micro-averaged F_1 score. In addition to this metric, we also report system performance in terms of Precision, Recall, and Accuracy.

Submission rules. Participating teams were allowed to submit up to four runs for each test set across the three subtasks. For each team's submissions, we retained only the highest score per task. Although the official results were derived exclusively from the blind test set, we streamlined the evaluation process by establishing four separate CodaLab competitions, one for each subtask¹. We are keeping the CodaLab for each subtask active even after the official competition has concluded. This is aimed at facilitating researchers who wish to continue training models and evaluating systems with the shared task's blind test sets. As a result, we will not disclose the ground truth labels for the test sets for any of the subtasks.

5 Shared Task Teams & Results

5.1 Participating Teams

Overall, we received 43 unique team registrations, 26 of them registered in the CodaLab, and only seven teams have submitted their results. These seven teams have submitted 263 valid entries during the testing phase. Specifically, 76 submissions for FlatNER were received from six teams, 168 submissions for NestedNER came from four teams, eight submissions for Gaza-Flat from one team, and 11 submissions for Gaza-Nested from 1

¹The different CodaLab competitions are available at the following links: Subtask 1, Subtask 2 and Subtask 3A, Subtask 3B.

Entity Name	NER Tag			NER				dNER	
2	c .	TRAIN	DEV	TEST	Total	TRAIN	DEV	TEST	Total
Cardinal	CARDINAL	1291	170	341	1802	1312	170	342	1824
Organization	ORG	10590	1488	3006	15084	13143	1863	3741	18747
Government	GOV	5689	848	1673	8210	5764	860	1695	8319
Date	DATE	10705	1592	3028	15325	11346	1691	3206	16243
Language	LANGUAGE	139	16	43	198	140	16	43	199
Group of people	NORP	3586	508	1008	5102	3952	551	1094	5597
Person	PERS	4519	611	1408	6538	5044	677	1565	7286
Occupation	0CC	3717	514	1090	5321	3822	532	1124	5478
GeoPolitical Entity	GPE	8052	1116	2395	11563	16113	2310	4676	23099
Country	COUNTRY	2911	436	834	4181	5744	835	1622	8201
Event	EVENT	1850	282	549	2681	1929	292	569	2790
Facility	FAC	560	86	179	825	777	116	227	1120
Building or ground	BUILDING-OR-GROUNDS	646	92	193	931	706	102	204	1012
Town	TOWN	4970	690	1460	7120	8374	1216	2431	12021
Loction	LOC	747	108	234	1089	985	141	317	1443
Continent	CONTINENT	65	10	23	98	133	23	57	213
Money	MONEY	172	22	33	227	172	22	33	227
Currency	CURR	15	2	8	25	176	24	41	241
Ordinal	ORDINAL	2739	445	889	4073	3444	544	1083	5071
Educational	EDU	440	49	134	623	821	109	229	1159
Time	TIME	309	33	84	426	311	33	84	428
Sports	SPO	11	2	8	21	11	2	8	21
Sport	SPORT	5	2	0	7	5	2	1	8
Land Region Natural	LAND-REGION-NATURAL	158	22	52	232	179	26	59	264
Cluster	CLUSTER	138	18	55	211	222	28	78	328
Quantity	QUANTITY	43	3	9	55	46	3	9	520
Unit	UNIT	6	1	2	9	46	4	11	61
State-or-Province	STATE-OR-PROVINCE	1146	159	372	1677	1292	179	421	1892
Non-Governmental	NONGOV	4030	566	1143	5739	4071	573	1158	5802
Neighborhood	NEIGHBORHOOD	78	5	29	112	87	5	30	122
Water-Body	WATER-BODY	76	14	18	108	88	14	21	122
Percent	PERCENT	92	11	33	137	92	12	33	137
Camp	CAMP	595	69	167	831	605	71	168	844
Path	PATH	52	6	18	76	52	6	18	76
Media	MED	2886	419	807	4112	2886	419	807	4112
Region-General	REGION-GENERAL	2330	37	67	379	2880	37	69	384
GPE_ORG	GPE_ORG	1000	161	316	1477	1036	167	325	1528
Website	WEBSITE	412	80	116	608	412	80	116	608
Commercial	COM	412	39	110	608	412	40	110	610
Celectial	CELESTIAL	438	0	2	4	439		2	4
Subarea - Facility	SUBAREA-FACILITY	91	16	23	130	96	16	23	135
	SUDAREA-PACILITY SCI	102	10	23	130	104	13	25 30	133
Medical-Science	REL	61	12	29	143 95	61	10	25	96
Religious			10			-			
ORG_FAC	ORG_FAC	87 67	12	19 29	113	87 70	7 12	19 29	113
Region-International	REGION-INTERNATIONAL			-	108				111
Entertainment	ENT	1	1	1	3	1	1	1	3
Boundary	BOUNDARY	15	4	3	22	15	4	3	22
Plant	PLANT	1	0	0	1	1	0	0	1
Law	LAW	368	47	90	505	368	47	90	505
Product	PRODUCT	61	8	17	86	62	8	19	89
Airport	AIRPORT	5	0	1	6	5	0	1	6
	Total	76034	10850	22173	109057	96947	13913	28068	138928

Table 1: Distribution of NER tags in WojoodNER-2024 Subtask1 (i.e., FlatNER) and Subtask2 (i.e., NestedNER) across the training (i.e., TRAIN), development (i.e., DEV), and test (i.e., TEST) splits for the WojoodNER-2024.

team. Table 2 provides details about the teams, their affiliations, and their tasks (1– FlatNER, 2– NestedNER, 3A– Gaza-Flat, and 3B– Gaza-Nested). Out of the seven teams, we received six description papers, which are all accepted for publication.

5.2 Baselines

For Subtask 1 and Subtask 2, we fine-tuned the AraBERT_{v2} (Antoun et al., 2020) pre-trained

model using subtask-specific training data for 20 epochs, with a learning rate of $1e^{-5}$ and a batch size of 8. To ensure optimal model performance, we incorporated early stopping with a patience setting of 5. After each epoch, we evaluated the model's performance and selected the best-performing checkpoints based on their performance on the respective development sets. We then present the performance metrics of the best-performing model on the test datasets.

Team	Affiliation(s)	Task
Addax (Issam AIT YAHIA, 2024)	Um6p College Of Computing, Morocco	1
Bangor University (Alshammari and Teahan, 2024)	Bangor University, UK	1
DRU (Hamoud et al., 2024; Hamdan et al., 2024)	Arab Center for Research and Policy Studies, Qatar	1,2,3
mucht (Abden and Mabaen 2024)	Technical University of Munich, Germany	1
mucAI (Abdou and Mohsen, 2024)	Helwan University of Cairo, Egypt	1
	King Abdulaziz City for Science and Technology (KACST),	
muNERa (Alotaibi et al., 2024)	Saudi Data and Artificial Intelligence Authority (SDAIA),	
	and King Salman Global Academy for Arabic Language (KSGAAL), Saudi Arabia	

Table 2: List of teams that participated in the WojoodNER-2024 subtasks.

5.3 Results

Table 3, Table 4, and Table 5 presents the leaderboards for Subtask 1–FlatNER, Subtask 2–NestedNER, and Subtask 3A–Gaza respectively, organized in descending order based on the micro- F_1 scores. The micro- F_1 score listed for each team reflects their highest score out of the four allowed submissions for each task.

Rank	Team	F_1	Pre.	Rec.
1	mucAI	91	91	90
2	muNERa	90	91	89
2	Addax	90	89	91
	Baseline-I (ARBERT _{v2})	$\overline{89}$	$-\bar{89}$	$-\bar{90}$
3	DRU - Arab Center	$\overline{87}$	$-\bar{86}$	$-\bar{86}$
4	Bangor	86	88	85

Table 3: Results of Subtask 1-FlatNER.

For FlatNER, the mucAI team (Abdou and Mohsen, 2024) achieved the highest F_1 score of 91, with muNERa (Alotaibi et al., 2024) and Addax (Issam AIT YAHIA, 2024) securing second place with 90, DRU taking third place with 87, and Bangor taking fourth place with 86. Notably, three teams outperformed our baseline, as shown in Table 3. The winning team mucAI(Abdou and Mohsen, 2024) surpassed the baseline by 2%. The performance gap between our baseline and the lowest-performing model is approximately 3%. Furthermore, the difference in F_1 scores among the teams is minimal, with a standard deviation of $\sigma = 1.94$.

Rank	Team	F1	Pre.	Rec.
	Baseline-I (ARBERTv2)	92	92	93
2	muNERa	$\overline{91}$	$-\bar{92}$	$-\bar{90}$
3	DRU - Arab Center	90	90	90

Table 4: Results of Subtask 2 – NestedNER.

For NestedNER, none of the teams outperformed the baseline. The muNERa team (Alotaibi et al., 2024) achieved the highest F_1 score of 91, but still 1% below the baseline, followed by DRU team (Hamoud et al., 2024) with a score of 90.

Rank	Team	F_1	Pre.	Rec.
1	DRU - Arab Center	73.7	71.9	75.6

Table 5: Results of Subtask 3 – Gaza-FlatNER.

For the open-track Gaza-FlatNER, only DRU team (Hamoud et al., 2024) reported their results with a recall of 75.9 and F_1 score of 73.5.

5.4 General Description of Submitted Systems

For Subtask 1 and Subtask 2, all models submitted to the shared task employed the transfer learning approach, utilizing pre-trained models trained on diverse data sources. For Subtask 3, LLMs with in-context learning techniques were utilized.

Addax (Issam AIT YAHIA, 2024) proposed a combined tagging approach that merges the main entity type and its subtypes into a single category (e.g., "B-GPE+B-COUNTRY" for "Palestine"). This method follows the IOB2 scheme for entity boundaries and simplifies training by focusing on a single combined tag per entity, integrating both main and subtype information. The model architecture utilizes a two-channel parallel hybrid neural network with an attention mechanism. It employs BERT-based model (AraBERTv0.2-Twitter) embeddings for contextualized word representations and consists of two distinct channels: one using Conv1D layers for local feature extraction and another with Bi-GRU layers to capture long-range dependencies. Additionally, an attention layer focusing on the most relevant input features has been added in each channel.

Bangor (Alshammari and Teahan, 2024) added a linear layer on top of a BERT-based model (bertbase-arabic-camelbert-mix) to classify each token into one of 51 different entity types and subtypes, as well as the "0" label for non-entity tokens. This linear layer maps the contextualized embeddings produced by BERT to the desired output labels.

muNERa (Alotaibi et al., 2024) team adapted Wojood dataset to fit the input requirements of the Translation between Augmented Natural Languages (TANL) framework (Paolini et al., 2021). The preprocessing steps included extracting hierarchical tags (parent, subtype, sub-subtype) and their spans using the IOB2 scheme. Each token and its corresponding labels were reformatted to align with the TANL framework's specifications. TANL was used for Subtask 1 and Subtask 2. In this framework, both input and output are structured in augmented natural languages and enclosed in square brackets (e.g., [token | entity type]). For nested entities, TANL can represent entity hierarchies, such as [token [token | entity type1] | entity type2]. They utilized two distinct TANL models for handling flat and nested entities. A decoder-encoder model (AraT5v2) is used as base for the TANL model. Additionally, they used a FastText (FT) classifier as a secondary tagger, first using TANL to detect spans and assign level-1 (parent) tags, and then applying the FT classifier to tag the detected spans with level-2 and level-3 tags. The best-performing TANL architecture was achieved without using FT.

mucAI (Abdou and Mohsen, 2024) team proposed a two-step methodology: joint vanilla finetuning followed by k-Neared Neighbor (KNN) at inference time. BERT (AraBERTv02) is used as the backbone for generating word embeddings. These embeddings are then fed into two multilayer perceptrons (MLP) that are trained jointly. The first head predicts one of the predefined 21 main entity tags. The second head predicts one of the predefined 31 sub-entities. A "Datastore" is constructed as a database that has a contextualized representation for each token alongside the label in each sentence in the training set. The "Datastore" was queried during inference to retrieve the k nearest neighbors based on a similarity score, derive the distribution of labels from these neighbors, and then interpolate this distribution with the main MLP model's distribution using an interpolation factor to obtain the final label probabilities.

DRU-Arab Center (Hamoud et al., 2024) proposed three strategies to deal with the Flat and Nested subtasks. (1) A single-layer approach, where they fine-tuned different BERT-based models to predict all types and subtypes in one shot, using a 103-length one-hot encoded vector for each

type and subtype, including the "0" tag. They experimented with GEMMA (Team et al., 2024), and AraBERTv2 (Antoun et al., 2020), and finetuned BLOOMZ-7b-mt on a high-quality Arabic dataset (Muennighoff et al., 2023). (2) Another attempt was the One×1 classifier method, which separated type and subtype classification by dedicating a model for each, training one instance of (AraBERTv2) exclusively for predicting main types and another instance for predicting subtypes. (3) In the One×4 Classifier Method, instead of only one model for subtypes, they trained four instances, each specialized in the sub-types of a specific group: GPE, ORG, FAC, LOC, as the other main types have no subtypes. Among these strategies, the One×1 approach achieved the highest performance on both Subtask 1 and Subtask 2.

For the open track Subtask 3, (Hamdan et al., 2024), DRU-Arab Center utilized LLMs (Cohere's Command R model (Command R Team)) and in-context learning to solve this task. the prompt design, they wrote a detailed system prompt that outlines the steps for tagging tokens according to the Wojood_{Fine} annotation guidelines. The prompt instructs the LLM to perform NER for Arabic text by predicting up to three levels of tags-high-level tags, subtypes, and specific subtypes for certain entities—while simplifying the task to two tag levels for practical purposes, and outputting predictions in CSV format; illustrative examples are provided to guide the model, and specific instructions ensure the correct application of the IOB2 schema and handle complex subtypes during post-processing. Command R's output quality issues included producing extra or missing tokens. To solve that, they post-processed the generated output to match the expected format by assigning the tag "0" to ground truth tokens without corresponding predicted tokens or hallucinated tags, and by converting the remaining format issues to the expected output.

6 Conclusion

In this paper, we present the outcomes of the second edition of WojoodNER shared task. The results from the participating teams highlight the ongoing difficulties in NER, yet it is encouraging to see that various innovative approaches, particularly those leveraging the power of language models, have proven effective in tackling this complex task. As we progress, we are dedicated to advancing research in this field. Our vision includes continuous efforts to improve Arabic NER, drawing on the valuable insights from WojoodNER-2024 and exploring new solutions. Additionally, we plan to expand the $Wojood_{Fine}$ corpus to encompass more dialects.

Limitations

Similar to WojoodNER-2023, WojoodNER-2024 aimed for the broadest possible coverage, primarily focusing on MSA data. This dataset used this year, $Wojood_{Fine}$, includes limited data from dialects. It only includes text from Palestinian and Lebanese Arabic. We plan to include the other dialects, especially the Syrian *Nabra* dialects (Nayouf et al., 2023) as well as the four dialects in the *Lisan* (Jarrar et al., 2023c) corpus. Additionally, the *Wojood^{Gaza}* dataset used in Subtask 3 covers only the initial phase of the Israeli War on Gaza, excluding the subsequent genocidal and starvation events.

Ethics Statement

The datasets provided for this shared task are derived from public sources, eliminating specific privacy concerns. The results of the shared task will be made publicly available to enable the research community to build upon them for the public good and peaceful purposes. Our datasets and research are strictly intended for non-malicious, peaceful, and non-military purposes.

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