Named Entity Recognition in COVID-19 tweets with Entity Knowledge Augmentation

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Abstract

The COVID-19 pandemic causes severe social and economic disruption around the world, raising various subjects that are discussed over social media. Identifying pandemic-related named entities as expressed on social media is fundamental and important to understand the discussions about the pandemic. However, there is limited work on named entity recognition on this topic due to the following challenges: 1) COVID-19 texts in social media are informal and their annotations are rare and insufficient to train a robust recognition model, and 2) named entity recognition in COVID-19 requires extensive domain-specific knowledge. To address these issues, we propose a novel entity knowledge augmentation approach for COVID-19, which can also be applied in general biomedical named entity recognition in both informal text format and formal text format. Experiments carried out on the COVID-19 tweets dataset and PubMed dataset show that our proposed entity knowledge augmentation improves NER performance in both fullysupervised and few-shot settings. Our source code are publicly available: https://github. com/kkkenshi/LLM-EKA/tree/master.

1 Introduction

The COVID-19 pandemic has led to significant social and economic upheaval globally, sparking various topics of conversation and debate on social media. Identifying pandemic-related entities mentioned on social media is crucial to highlight these discussions. However, there are limited named entity recognition data annotated with a focus on COVID-19 or public health research, making it difficult for pandemic-related analysis and NER model training (Tjong Kim Sang and De Meulder, 2003; Pradhan et al., 2013; Strauss et al., 2016; Hou et al., 2020; Jiang et al., 2022).

To address the challenges posed by the limited availability of annotated data, several data augmen-

tation methods have been proposed to improve the performance of NER models. Traditional data augmentation methods, such as back-translation (Sennrich et al., 2016), synonym replacement (Wei and Zou, 2019), shuffle with segments (Dai and Adel, 2020), and the methods that rely on modelgenerated data (Ding et al., 2020; Zhou et al., 2022b), have been applied to enhance the diversity and robustness of training data. However, as shown in Figure 1, they either overlook the syntactic structure of the sentence or perform poorly in domainspecific contexts. For instance, DAGA (Ding et al., 2020) generates sentences with syntactic irregularities, which limits its effectiveness in NER tasks that depend on the precise syntactic and semantic structure of each token to accurately identify entities and their types. MELM (Zhou et al., 2022b) tends to ignore the sentence context during substitution and exhibits limited scalability when adapting to new entities. LLM-DA (Ye et al., 2024), despite its flexibility, shows suboptimal performance in domain-specific scenarios, frequently generating vague or contextually inappropriate entity, especially when handling fine-grained entity types.

Recent advancements in large language models (LLMs) have significantly improved performance in NER tasks across both general and domainspecific scenarios (Huang et al., 2022; Yang et al., 2022; Chen et al., 2023a; Meoni et al., 2023; Sharma et al., 2023; Bogdanov et al., 2024). These works inspire the development of more tailored augmentation frameworks that align LLMs with fine-grained entity knowledge. Building upon these advancements, the broader success of large language models in various NLP tasks has further expanded the possibilities for enhancing NER through more flexible and generalizable training paradigms. By leveraging their superior text representation capabilities, we propose a LLM-based Entity Knowledge Augmentation (LLM-EKA) to enrich the COVID-19-related knowledge of the

Original Sentence Earth, Wind & Fire BLASTING at the [COVID vaccine] vaccina site!! DAGA [Heart]_vaccina per shit kids month never his eyes @BrianWGR sushi @ClupterObert eyes study daily Earlier @JAMA_current yet liked on conveyor individuals, bug Earth support eating and not left cash hospices. MELM Earth, Wind & Fire BLASTING at the [vaccinvid vaccina]_vaccina site!! LLM-DA Earth, Wind & Fire BLASTING at the [flu shot]_vaccina site!! LLM-EKA [VaxInsta]_vaccina offering a ray of hope amidst the chaos of COVID-19. Stay safe, get vaccinated!

Figure 1: Examples of various data augmentation methods in few-shot settings. The named entities are [bold].

models, which can also be applied into other domain-specific NER models.

LLM-EKA consists of demonstration selection, entity augmentation, and instance augmentation, which effectively aligns LLMs to the domain-specific knowledge. The demonstration selection aims to extract informative examples that are used as demonstrations for instance augmentation. The entity augmentation is applied to obtain domain-specific entities via large language models. The instance augmentation generates additional domain-specific training instances via prompts according to the selected demonstrations and augmented domain-specific entities.

The results of experiments carried out on both the METS-CoV benchmark and the BioRED benchmark show that the NER models equipped with the proposed LLM-EKA outperform the baseline models in the fully-supervised and few-shot settings. The main contributions of this work are summarized as follows:

- We investigate named entity recognition from medical research perspectives that contribute to public health concerns.
- We propose a novel framework of entity knowledge augmentation for named entity recognition in COVID-19 tweets, which can also be applied into other domain-specific NER models.
- Our final model, equipped with the proposed entity knowledge augmentation, achieves state-of-the-art results on benchmarks in both

fully-supervised and few-shot settings. The codes will be released.

2 Related Work

Named Entity Recognition is widely investigated as a conventional task in NLP. Recent work has focused on specific domains, which are often limited to small-scale training data.

Domain Transfer Domain transfer aims to alleviate the data scarcity issue by transferring knowledge from source domains to target domains. This line of research on NER enhances the generalization of models by aligning the entity knowledge of source domains with the target domains and enhances adaptability by mapping the entity label space between the source and target domains (Daumé III, 2007). Additionally, label embeddings are used as features to map label types across different domains, enabling cross-domain transfer (Kim et al., 2015). A label-aware dual transfer learning framework that uses a variant of the Maximum Mean Discrepancy (MMD) algorithm has been proposed (Wang et al., 2018). Cross-Domain NER algorithms enhance model generalization by aligning entity knowledge from the source domain with the target domain (Lee et al., 2018; Lin and Lu, 2018; Yang et al., 2018), and cross-domain language modeling and a novel parameter generation network have been utilized to perform knowledge transfer across domains and tasks (Jia et al., 2019). A novel architecture for multi-domain NER has been presented that employs shared and private domain parameters along

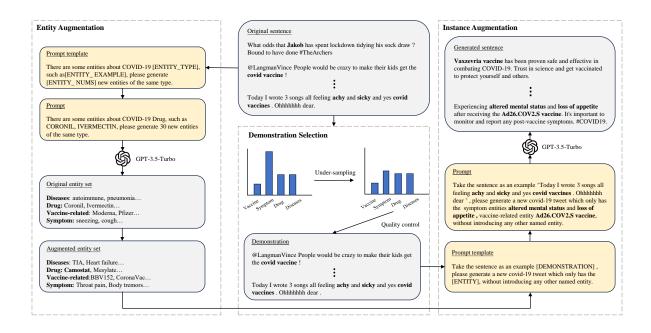


Figure 2: Framework of LLM-based Entity Knowledge Augmentation.

with multi-task learning to enhance model robustness across various text genres (Wang et al., 2020). Moreover, some related works have been conducted in few-shot settings (Cui et al., 2021; Ma et al., 2022; Ding et al., 2022; Chen et al., 2023b; Fang et al., 2023). However, these methods are based on the assumption that the label spaces between the source domain and target domain are aligned.

Data Augmentation Data augmentation methods aim to directly expand the scale of training data to alleviate the data scarcity. Language generation models trained on labeled data have been used to generate samples for few-shot scenarios, achieving significant improvements in entity recognition using both supervised and unsupervised methods (Ding et al., 2020). Similarly, simple token-level augmentation techniques have been proposed by adapting sentence-level task augmentation strategies, which have proven especially effective in enhancing NER performance in fewshot settings, particularly with small-scale training datasets (Dai and Adel, 2020). The label-tag misalignment issue in few-shot named entity recognition has been tackled by explicitly injecting NER labels into sentence context, and further improvements have been made in multilingual settings using code-mixing techniques (Zhou et al., 2022b). Moreover, LLMs have been leveraged to generate a large quantity of diverse and high-quality new data

for NER (Ye et al., 2024). However, these methods suffer from a lack of domain-specific knowledge and are not well-suited to NER in domains that require extensive expertise.

3 Methodology

As shown in Figure 2, the framework of LLM-EKA consists of demonstration selection, entity augmentation, and instance augmentation.

3.1 Named Entity Recognition Model

Named entity recognition is modeled as a sequence labeling task, where the input is a sequence of words, $[x_1, x_2, \ldots, x_n]$, and the output is a sequence of labels, $[y_1, y_2, \ldots, y_n]$, where n is the length of the input sentence. We use the BIO labeling system for NER.

We use a pre-trained language model to obtain the hidden representation, which transforms the input tokens into their respective hidden representations, $[h_1, h_2, \ldots, h_n]$. Subsequently, the hidden representation of each word is projected into a logit space, $o_i = Wh_i + b$, where W and b are the learnable parameters. The logits o_i represent scores for each potential label associated with the word x_i . The predicted label for each word y_i is then determined by applying the $\arg\max_c o_{i,c}$, where c indexes the set of possible labels. The models are optimized by

minimizing the cross-entropy loss:

$$\mathcal{L} = -\frac{1}{n} \sum_{i=1}^{n} \log p(y_i \mid x_i), \tag{1}$$

where $p(y_i \mid x_i)$ is the probability assigned to the true label by the model, which is obtained via a softmax operation over the logits.

3.2 Demonstration Selection

Given the training set, $S = \{s_1, s_2, \dots, s_n\}$, where each instance s_i has a set of entities E_i , we design different demonstration selection algorithms to fully-supervised settings and few-shot settings, respectively.

In fully-supervised settings, we perform undersampling to filter out instances that contain the over-represented category, which balances the entity distribution, preventing model bias. A maximum threshold t on the number of entities per instance is taken to reduce complexity and mitigate noise, yielding a quality-controlled subset:

$$S_q = \{ s_i \in S \mid |E_i| \le t \},$$
 (2)

where $|E_i|$ denotes the number of entities in instance s_i , where domain-specific entities have higher priority. The demonstration set for fully-supervised settings, $S_{\text{demo-full}}$ satisfies that each $s_i \in S_q$ should contain domain-specific entities:

$$S_{\text{demo-full}} = \{ s_i \in S_q \mid E_i \text{ has domain-specific entities} \}$$
 (3)

In few-shot settings, we apply Algorithm 1 to sample a k-shot demonstration set. This algorithm ensures that each domain-specific entity appears at least k times in the selected subset while preventing any entity type from being over-represented. ¹

3.3 Entity Augmentation

In few-shot NER tasks, particularly when dealing with domain-specific entities, entity augmentation plays a crucial role in addressing the scarcity of domain-specific annotated entities. We leverage large language models to expand the knowledge of domain-specific entities with prompts. The prompt typically follows a template such as: "There are some entities about COVID-19 [ENTITY TYPE] such as [ENTITY_EXAMPLE]. Please generate [ENTITY_NUMS] new entities of the same type."

Algorithm 1 Demonstration selection for k-shot settings

```
Input: Training set S = \{s_1, \ldots, s_n\}
             Entity type set C = \{c_1, \ldots, c_m\}
             Tolerance \alpha
Output: Demonstration set S_{\text{demo-few}} with k \leq C(c) \leq
      \alpha k, \ \forall c \in \mathcal{C}
 1: Initialize S_{\text{demo-few}} \leftarrow \emptyset
 2: Initialize counter C(c) \leftarrow 0, \ \forall c \in \mathcal{C}
 3: Shuffle S randomly
 4: for each instance s_i \in S do
 5:
           \Delta(c) \leftarrow 0, \ \forall c \in \mathcal{C}
 6:
           for each entity type c \in s_i do
 7:
                if c \in \mathcal{C} then
 8:
                      \Delta(c) \leftarrow \Delta(c) + 1
 9:
                end if
10:
           Initialize add \leftarrow True
11:
12:
           for each c \in \mathcal{C} do
13:
                 if C(c) + \Delta(c) > \alpha k then
14:
                      add ← False, break
15:
                 end if
16:
           end for
17:
           if add then
18:
                for each c \in \mathcal{C} do
19:
                      C(c) \leftarrow C(c) + \Delta(c)
20:
21:
                 S_{\text{demo-few}} \leftarrow S_{\text{demo-few}} \cup \{s_i\}
22:
           end if
           if \forall c \in \mathcal{C}, \ C(c) \geq k then
23:
24:
                break
25:
           end if
26: end for
27: return S<sub>demo-few</sub>
```

where the [ENTITY_TYPE] is the domain-specific entity type, while [ENTITY_EXAMPLE] is a concrete instance drawn from the training samples, [ENTITY_NUMS] is the numerical quantity of new entities to be generated.

The approach encompasses two primary strategies for entity augmentation: straightforward strategy and iterative. In the straightforward approach, all available entity samples are input into the prompt at once, allowing the model to generate a set of new entities in a single operation. While this method is simple and efficient, it may lead to information overload if the prompt becomes overly lengthy, potentially impacting the quality of the generated entities due to diminished focus on individual entity characteristics. To address this limitation, iterative strategy is introduced, where the entity samples are divided into smaller batches and fed into the model over multiple iterations. The strategy enable LLMs to concentrate on a narrow subset of entities at each step.

 $^{^{1}}$ In our implementation, we set the tolerance parameter α to 1.3.

Model	Loc.	Org.	Per.	Sym.	Vacc.	Dise.	Drug	Avg
CRF	76.37±0.62	54.64±2.08	64.43±1.59	74.05±0.56	84.85±0.82	73.61±0.44	77.34±1.60	71.58±0.54
BiLSTM + CRF	79.25±0.59	62.39±0.97	72.41±0.44	79.14±0.51	88.72±0.62	74.89±1.28	79.60±0.71	76.38±0.22
BiLSTM + CLSTM + CRF	81.26±1.19	63.21±0.93	77.49±1.67	79.14±0.53	87.85±0.43	75.61±0.76	81.27±0.65	77.63±0.40
BiLSTM + CCNN + CRF	82.15±0.44	62.79±0.91	81.38±0.44	78.12±0.51	89.11±0.36	76.12±0.76	80.41±0.58	78.10±0.19
BART-large	80.04±4.74	64.66±8.86	81.60±4.93	74.27±4.45	81.21±6.20	71.24±1.90	80.61±2.90	75.56±5.04
BERT-large	84.63±1.38	73.30±1.38	88.25±0.52	80.12±0.55	89.16±1.58	76.52±1.11	86.05±1.06	82.05±0.24
RoBERTa-large	85.85±2.12	73.78±0.72	86.79±0.44	81.32±0.67	90.42±1.12	76.84±0.57	86.79±0.78	82.55±0.27
COVID-TWITTER-BERT	85.68±0.92	76.27±0.64	91.29±0.42	81.85±0.53	90.44±0.94	77.48±0.81	86.35±0.96	83.88±0.20
+DAGA	86.67±0.10	75.74±0.29	89.42±0.55	82.05±0.10	88.52±0.42	76.28±0.44	84.78±1.76	83.20±0.12
+MELM	83.66±0.24	75.07±0.32	90.07±0.84	80.45±0.61	88.04±1.63	76.95±1.27	84.37±0.15	82.43±0.15
+LLM-DA	85.78±0.66	75.16±0.51	89.82±0.95	80.88±0.38	88.90±0.70	76.75±0.72	86.49±0.55	82.96±0.17
+LLM-EKA-straight	86.33±0.57	76.98±0.27	90.62±0.58	82.16±0.21	90.46±1.05	77.46±0.88	87.12±0.95	84.08±0.10
+LLM-EKA-iterative	86.78±1.00	76.69±0.53	90.63±0.51	82.35±0.43	92.05±0.52	77.72±0.80	87.14±0.45	84.32±0.10

Table 1: Results on test data in METS-CoV. LLM-EKA-straight represents the model enhanced with the straightforward strategy in entity augmentation. LLM-EKA-iterative represents the model enhanced with the iterative strategy in entity augmentations. The best scores are **bold** and the second best scores are underlined.

3.4 Instance Augmentation

Building upon the expanded entity set obtained through Entity Augmentation, we introduce Instance Augmentation to generate diverse, contextually grounded textual instances that integrate the augmented entities while preserving contextual coherence and domain-specific relevance. We generate new COVID-19 tweets by querying LLMs using a prompt template "Take the sentence as an example [DEMONSTRATION], please generate a new COVID-19 tweet which only has the [ENTITY], without introducing any other named entity." The prompts have demonstration slot, [DEMONSTRA-TION], filled by sentences outputted from the demonstration selection, aiming to guide LLM to generate tweets with high quality and consistency in structure and style. The entity slot, [ENTITY], are filled by domain-specific entities obtained from the entity augmentation.

Although template design and context constraints guide LLM to generate text that meets expectations, the inherent randomness of language models may still cause the generated results to deviate from the target. To alleviate the problem, we discard the sentences that contain entities outside the predefined entity set. This prevents the introduction of irrelevant or noisy entities.

4 Experiments

We conduct experiments in fully-supervised settings and few-shot settings by comparing our methods with recent data augmentations. Additionally, we show the performance of recent LLM-based methods on COVID-19 and biomedical NER tasks to demonstrate the effect of our proposed methods.

4.1 Data

The experiments are conducted on the METS-CoV benchmark which contains 7000 tweets with 7 entity types (Zhou et al., 2022a), including 4 medical entity types: disease, drug, symptom and vaccine, and 3 general entity types: person, location and organization. In order to demonstrate that our model can be generalized to other biomedical NER task, we also conduct the experiments on BioRED benchmark (Luo et al., 2022), a set of 600 PubMed abstracts including 6 entity types: disease or phenotypic feature, chemical entity, gene or gene product, organism taxon, sequence variant, cell line.

4.2 Baselines

We compare our models to traditional NER methods and the models based on pre-trained language model. The traditional NER models include CRF, BiLSTM + CRF, BiLSTM + CLSTM + CRF, and BiLSTM + CCNN + CRF, where CLSTM and CCNN are the modules of encoding character information with LSTM and CNN, respectively. For pretrained language models, we utilize BERT-large, RoBERTa-large, and BART-large. Additionally, in order to make the models with ability of handling tweets, we additionally take several recent data augmentation methods to base NER models. In addition, we include comparisons with LLMbased NER methods, which leverage the generative capabilities of large language models for few-shot name entity recognition. The data augmentation are summarized as follows:

 DAGA (Ding et al., 2020) linearize each labeled sentence and training a lightweight single-layer LSTM to capture their joint dis-

Model	k	Loc.	Org.	Per.	Sym.	Vacc.	Dise.	Drug	Avg
COVID-TWITTER-BERT		02.85±03.21	06.35±08.82	10.13±11.83	19.53±08.24	08.64±03.78	21.75±11.31	41.63±11.64	16.84±06.03
+DAGA		02.15±02.62	03.66±04.53	04.58±05.81	21.09±06.32	10.73±04.85	23.35±11.20	39.64±15.18	15.50±04.48
+MELM	5	13.46±08.37	16.66±09.64	19.78±17.51	27.05±04.58	13.20±04.95	30.66±05.74	52.05±03.64	24.54±04.31
+LLM-DA	3	23.21±15.32	21.03±04.90	10.76±06.47	44.23±11.00	27.13±08.37	38.84±02.01	59.93±03.78	34.55±04.42
+LLM-EKA		47.67±02.82	32.60±04.65	41.88±11.08	36.24±04.60	37.94±01.11	44.65±03.40	64.52±05.25	41.73±02.61
w/self-verification		48.18±07.40	32.63±08.76	36.60±14.78	46.23±5.74	35.55±05.59	44.69±05.52	65.78±03.47	43.65±06.91
COVID-TWITTER-BERT		21.09±15.10	09.08±07.17	24.56±19.22	28.13±09.32	25.38±14.38	34.94±21.55	51.23±19.80	27.19±14.24
+DAGA		31.00±09.79	12.52±07.68	33.58±09.71	39.73±05.02	33.01±08.85	52.02±01.98	62.65±02.98	37.82±01.28
+MELM	10	43.48±04.67	28.27±00.70	53.23±07.26	34.89±02.22	28.59±00.96	50.67±00.02	61.37±00.55	41.21±01.29
+LLM-DA	10	54.08±04.38	33.32±02.75	48.29±10.68	45.86±03.22	38.85±06.02	49.40±04.67	65.90±02.76	46.68±02.09
+LLM-EKA		42.69±01.07	35.94±00.41	59.72±02.47	44.21±00.99	58.00±01.74	51.70±00.34	63.65±00.09	49.54±00.57
w/ self-verification		59.96±03.58	38.49±02.17	50.33±07.91	44.77±02.35	57.19±04.79	53.08±02.93	67.13±02.85	50.50±02.32
COVID-TWITTER-BERT		45.48±08.50	36.02±02.15	48.06±04.16	50.31±02.47	50.37±05.30	59.16±01.60	68.27±01.19	50.13±02.70
+DAGA		53.59±04.19	33.98±03.98	55.73±03.56	53.30±02.89	46.36±03.99	52.87±02.15	66.18±03.76	51.66±02.06
+MELM	20	61.19±04.52	45.33±02.90	76.47±05.76	55.16±02.07	50.99±02.15	54.45±01.41	66.60±03.52	56.61±00.81
+LLM-DA		65.72±02.47	45.21±02.87	58.36±03.18	50.56±00.30	56.98±04.06	54.24±06.00	66.79±00.17	55.28±02.59
+LLM-EKA		57.41±01.00	42.84±01.49	66.96±02.24	54.75±02.11	55.47±04.79	59.25±00.90	65.83±00.29	56.60±00.33
w/ self-verification		68.75±01.17	45.74±02.12	63.65±03.24	53.23±03.11	63.04±03.84	57.65±02.38	70.66±02.27	58.72±01.18

Table 2: Results of COVID-TWITTER-BERT with various data augmentation methods on METS-CoV test data in k-shot setting. The best scores are **bold** and the second best scores are <u>underlined</u>.

tribution via next-token prediction, which is used to generate high-quality synthetic annotated data.²

- MELM (Zhou et al., 2022b) predicts masked entity tokens based on their corresponding NER tags to generate diverse and labelconsistent synthetic sentences.³
- LLM-DA (Ye et al., 2024) leverages large language models through structured prompting and multi-level augmentation by contextual rewriting, entity replacement, and noise injection.

COVID-TWITTER-BERT (Müller et al., 2020) and PubMedBERT (Gu et al., 2021) are adopted as base NER models for METS-CoV and BioRED, respectively.

4.3 Settings

We apply GPT-3.5-turbo for the knowledge argumentation with the temperature of 1, fully leveraging the diversity generation capabilities. We set the batch size to 8 and employ the AdamW optimizer with a learning rate of 3e-5. The models are trained in 100 epochs. Micro F1 scores are used as our evaluation metrics. We set up 5-shot, 10-shot, and 20-shot settings for few-shot experiments. All the models are trained on one 24G GPU.

4.4 Fully-supervised

Table 1 shows the results on the test data across different models. Pre-trained language models BERT and RoBERTa significantly outperforms the traditional LSTM models with CRF. COVID-TWITTER-BERT outperforms RoBERTa because it has the ability to represent the COVID-19 tweets with help of the pre-training on tweets. Equipped with our proposed entity knowledge augmentation, the final model achieve the best results.

Incremental Augmentation We experiment with two augmentation approaches: LLM-EKA-straight and LLM-EKA-iterative. As shown in Table 1, both LLM-EKA approaches outperforms baselines, achieving an average score of 84.08 and 84.32, respectively. By incrementally refining entity knowledge, LLM-EKA-iterative reduces noise and prevents LLMs information overload, leading to enhanced performance and better handling of long-distance dependencies.

Entity Type We perform a fine-grained analysis of the performance of different entity types across models. LLM-EKA-iterative show significant improvements in recognizing domain-specific entities, particularly for drugs (87.14 F1) and vaccine-related entities (92.05 F1). This suggests that our knowledge augmentation methods, especially with iterative refinement, enhance the model's ability to discern and accurately classify entities within the context of COVID-19 tweets.

²https://ntunlpsg.github.io/project/daga/

³https://github.com/RandyZhouRan/MELM/

Model	k	Cell.	Chem.	Dise.	Gene.	Orga.	Sequ.	Average
PubMedBERT		58.24±09.42	42.05±23.65	07.80±06.10	44.67±15.91	30.19±11.24	40.44±10.43	35.86±08.48
+DAGA		06.62±06.58	32.35±06.66	10.22±07.88	25.53±05.31	35.05±11.49	40.93±08.77	26.05±05.42
+MELM	5	32.19±12.11	47.25±12.45	21.84±03.85	55.10±05.43	49.78±07.89	49.13±08.62	43.90±03.64
+LLM-DA	5	52.43±09.36	68.49±04.13	27.75±08.44	66.39±02.23	19.03±15.09	44.30±06.41	51.53±02.24
+LLM-EKA		66.14±07.07	70.42±02.97	42.86±02.16	71.97±00.41	66.71±09.92	56.65±05.14	62.79±00.61
w/ self-verification		67.14±06.72	71.27±02.48	47.13±03.44	72.86±00.87	69.07±06.91	54.05±01.66	64.33±01.15
PubMedBERT		68.77±03.13	67.39±04.39	23.30±04.01	57.96±10.22	53.48±07.22	47.18±11.93	51.83±04.22
+DAGA	10	47.22±07.29	62.19±01.59	22.40±04.41	52.37±04.02	53.20±10.52	39.85±02.89	46.85±03.28
+MELM		48.89±08.95	71.75±01.55	30.37±02.46	63.23±03.18	54.23±08.01	48.67±05.69	53.66±02.23
+LLM-DA		61.20±09.67	74.64±01.51	37.61±01.86	72.00±05.80	61.84±06.60	47.97±10.39	61.22±02.44
+LLM-EKA		68.19±12.54	74.04±01.82	54.24±02.68	73.45±02.57	77.54±04.56	51.92±03.13	67.51±00.80
w/ self-verification		66.96±02.97	76.14±01.57	57.23±01.50	74.73±01.57	76.68±02.68	54.11±00.74	69.05±00.74
PubMedBERT		54.74±03.32	75.95±00.18	47.98±00.16	70.32±00.85	85.76±01.18	59.14±01.46	66.27±00.40
+DAGA	20	52.21±14.48	75.14±02.12	41.32±01.80	67.95±01.83	83.29±01.95	50.92±01.75	62.84±00.47
+MELM		58.87±18.83	77.95±01.49	52.20±02.23	72.32±04.72	80.53±01.03	55.79±03.06	67.73±02.75
+LLM-DA		70.00±12.20	78.24±01.44	45.73±01.47	74.68±03.13	82.34±01.54	55.93±01.03	67.47±00.96
+LLM-EKA		73.93±01.33	71.93±01.77	58.56±01.38	78.51±01.31	79.64±04.06	62.49±01.82	70.79±00.18
w/ self-verification		67.81±02.67	77.98±00.62	55.32±00.79	82.21±01.07	75.09±05.35	62.49±04.66	72.24±00.04

Table 3: Results of PubMedBERT with various data augmetations on BioRED test data in k-shot setting. The best scores are **bold** and the second best scores are underlined.

4.5 Few-shot

Table 2 and Table 3 show the performances of various methods in k-shot settings, respectively. In few-shot settings, our method consistently surpasses existing approaches across multiple datasets. On the METS-CoV dataset, which includes both general and domain-specific entities, our approach improves performance by 10–15 points in the 5-shot and 10-shot settings, demonstrating its effectiveness in capturing domain-specific knowledge. Similarly, on the BioRED dataset, which covers diverse biomedical entity types, our method achieves notable gains, outperforming prior methods by a significant margin, particularly in extremely low-resource conditions.

Data Domains METS-CoV contains informal, user-generated text with abbreviations and conversational language, while BioRED consists of well-structured biomedical literature with formal terminology. The difference impacts performance gains. in BioRED, our method achieves substantial improvements. In contrast, METS-CoV informal style introduces greater linguistic variability, making augmentation less effective. Moreover, METS-CoV includes three general entity types (person, organization, location), which are more common across datasets and less domain-specific, further

Model	5-she	ot	10-shot		
Model	METS-CoV	BioRED	METS-CoV	BioRED	
GPT-NER	23.96	30.81	35.88	35.68	
RT	34.59	32.43	35.54	39.64	
ours	43.65	64.33	50.50	69.05	

Table 4: Results on METS-CoV and BioRED test data in 5/10-shot settings. The best scores are **bold** and the second best scores are underlined.

affecting augmentation consistency.

Self-verification Self-verification mechanism plays a crucial role in improving model robustness in few-shot settings by filtering out domainirrelevant augmentations (e.g., non-COVID-19-related disease entities such as *Brucellosis* or drug entities like *Chloroquine*) while enforcing precision in domain-specific terminology. However, as training data scales to 20-shot, the increased lexical diversity (e.g., formal names like *BNT162b2* and regional variants) enables the mechanism to better distinguish noise from valid expressions.

4.6 Comparison to LLM-based Models

The LLM-based models are summarized as follows:

 GPT-NER (Wang et al., 2023) reformulates NER as generation, prompt an LLM to wrap entities with special tokens, retrieve entity-level or sentence-level kNN demonstra-

⁴We take LLM-EKA-iterative as our model LLM-EKA in few-shot experiments.

Method	Result
Case A	Having intense [allergies] _{symptom} and waking up every morning with a [sore throat] _{symptom} and hoping by noon it goes away be it was just from drainage and not COVID.
LLM-DA LLM-EKA	Having intense allergies and waking up every morning with a [sore throat] _{symptom} and hoping by noon it goes away be it was just from drainage and not COVID. Having intense [allergies] _{symptom} and waking up every morning with a [sore throat] _{symptom} and hoping by noon it goes away be it was just from drainage and not COVID.
Case B	Um, actually, we do vaccinate healthy people against diseases— [Polio] _{disease} , [Tetanus] _{disease} , [MMR] _{disease} , [pneumonia] _{disease} , to name a few—everyone has the potential to be at risk from COVID.
LLM-DA	Um, actually, we do vaccinate healthy people against diseases—Polio, [Tetanus] _{drug} , MMR, [pneumonia] _{disease} , to name a few—everyone has the potential to be at risk from COVID.
LLM-EKA	Um, actually, we do vaccinate healthy people against diseases— [Polio] _{disease} , [Tetanus] _{disease} , [MMR] _{disease} , [pneumonia] _{disease} , to name a few—everyone has the potential to be at risk from COVID.

Table 5: Examples of NER in 5-shot setting.

tions for few-shot guidance, and apply self-verification to reduce hallucination.⁵

 RT (Li and Zhang, 2023) enhances few-shot medical NER by retrieving relevant demonstrations via entity-aware KNN, followed by step-by-step entity prediction using chain-ofthought prompts.⁶

Table 4 shows the results of LLM-based NER models in few-shot settings. Although recent LLMbased NER methods such as GPT-NER and RT demonstrate promising potential in few-shot scenarios, their practical effectiveness on challenging benchmarks like METS-CoV and BioRED reveals several critical limitations. In 5-shot setting, GPT-NER achieves micro F1 scores of 23.96 on METS-CoV and 30.81 on BioRED, while RT slightly outperforms it with 34.59 and 32.43, respectively. However, both models lag significantly behind our methods, which achieves 43.65 on METS-CoV and 64.33 on BioRED in the same setting. In 10-shot setting, the performance gap becomes more significant. It shows that general LLM hardly captures the domain-specific knowledge, which is the focus of our proposed methods.

4.7 Case Study

Table 5 shows the outputs across LLM-DA and LLM-EKA on COVID-19 tweets dataset. LLM-DA fails to recognize certain entity and assigns incorrect types. In Case A, it fails to detect the standalone symptom entity *allergies*, while by incorporating entities knowledge-enhanced prompts, our method achieves superior recognition of domain-specific terminology. In Case B, LLM-DA not only fails to label *Polio* and *MMR* but also misclassifies *Tetanus* as a drug, while LLM-EKA effectively leverages entities contextual semantics and structural information to pinpoint the boundary and type of entities with high precision.

5 Conclusion

We present a novel LLM-based entity knowledge augmentation for named entity recognition in COVID-19 tweets for public health research. LLM-EKA leverages the sophisticated contextual reasoning capabilities and extensive knowledge base of LLMs to augment entity knowledge and improve recognition performance. Our proposed methods are model-agnostic and can be adapted to enhance NER models in other biomedical subdomains. The experimental results show that our proposed data augmentation methods outperform previous work in fully-supervised and few-shot settings. In few-

⁵https://github.com/ShuheWang1998/GPT-NER

⁶https://github.com/ToneLi/ RT-Retrieving-and-Thinking

shot settings, our LLM-EKA is capable of addressing the challenges associated with scarce annotated data and the need for domain-specific expertise.

Limitations

LLM-EKA current applicability is limited to the biomedical domain and the framework relies on a fixed base model, meaning its performance is inherently constrained by the capabilities and representation limits of the underlying encoder. Furthermore, our use of proprietary LLMs via API introduces dependence on third-party services.

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