BERT-based language Model for Extracting Drug Adverse Events from Social Media

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Highlights

- **Problems:** During Covid-19 pandemic, social media platforms like Twitter, Facebook have emerged as valuable resources for real-time pharmacovigilance. However, extracting drug adverse events accurately and efficiently from social media poses challenges in both natural language processing research and the pharmacovigilance domain.

- **Questions:** Could we utilize large language models to extract adverse drug event terms from social media data and thereby enhance drug safety surveillance?

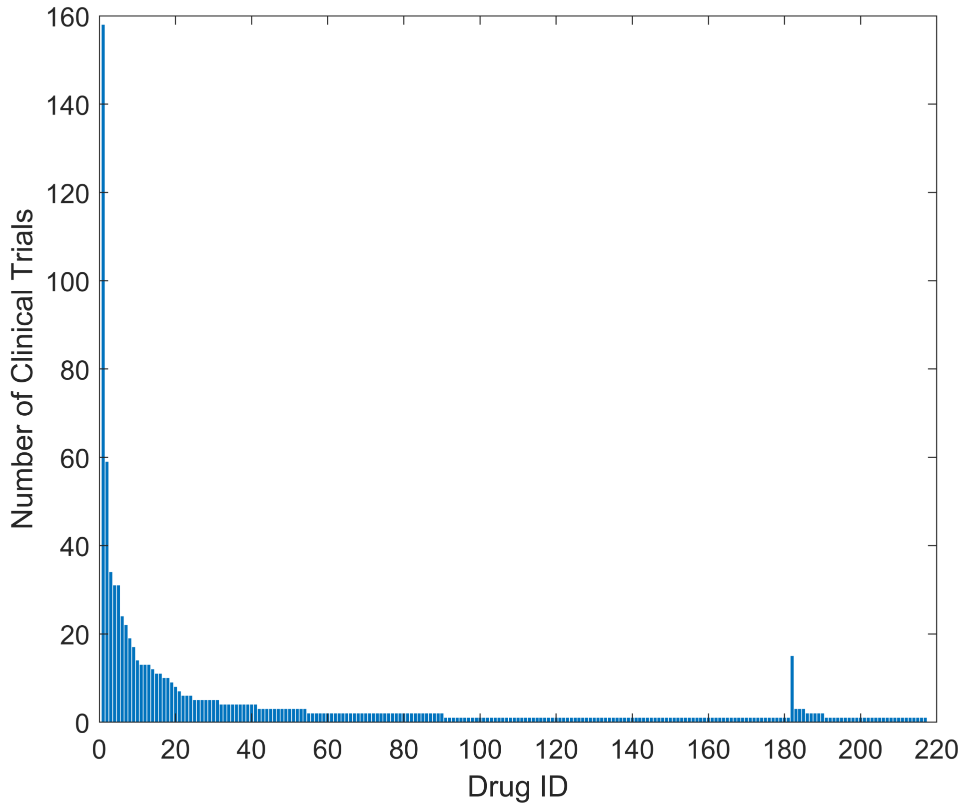
- **Findings:** Our study not only showcases the effectiveness of BERT-based language models in accurately identifying drug adverse events in social media data but also addresses the imperative for a comprehensive implementation study design and evaluation.

- **Meanings:** Our study contributes to advancing pharmacovigilance practices and methodologies, particularly in the context of emerging information sources like social media.

Background

➢ Coronavirus disease 2019(COVID-19) caused by the SARS-CoV-2 virus, is a highly contagious respiratory illness that emerged in late 2019 and led to a global pandemic.

- ❑ The number of patients is huge.
- ❑ A plethora of drugs are currently being utilized for COVID-19 patients.
- ❑ Urgent need for Drug safety evaluation for COVID-19 Patients.



217 Drugs from 577 clinical trials registered on ClinicalTrials.gov for Covid-19 treatment

Citation:10.1038/s41598-021-93500-5

Background

- ➢ Option 1: Drug Safety evaluation with FEARS:
  - ❑ Adverse Event Source : FDA Adverse Events Report Systems (FAERS)
  - ❑ Limitations:
    - Over 90% data are sponsor reported.
    - Population are not COVID-19 Patients specifically.
- ➢ Option 2: Drug Safety evaluation with Social Media Data.
  - ❑ Features:
    - Real time monitoring
    - For COVID-19 patients

Background

Given the urgency of the Covid-19 pandemic, A remarkable number of drugs have been considered for treating Covid-19 but the efficacy of drugs remain unclear.

	Social Media (Tweets)	FAERS
Timeliness	Real-time information as patients can post their experiences immediately	Result available after the completion of the trial
Volume and Scale	Huge volume generate from a diverse and global population	Limited to number of participants with limited demographic diversity
Data quality	Variable quality, as posts maybe subjective and can contain inaccuracies or exaggerations	High quality, as it is a regulated system with structure data collection
Data Structure	Unstructured	Structured
Use Cases	Useful for early signal detection, monitoring real-world use of medications	Essential for establishing the safety and efficacy of new medications in a controlled and rigorous manner

Background

- Drug safety assessment with Social media data poses a tough challenge.
  - Informal and unstructured nature of social media data
  - Huge data volume
  - Lack of standardization
  - Causal relationship between a drug and an adverse event
  - NLP challenges with informal language like for slang, abbreviations, and misspellings in social media posts
  - Traditional search and filtering techniques are insufficient for extracting and normalizing adverse events from social media data

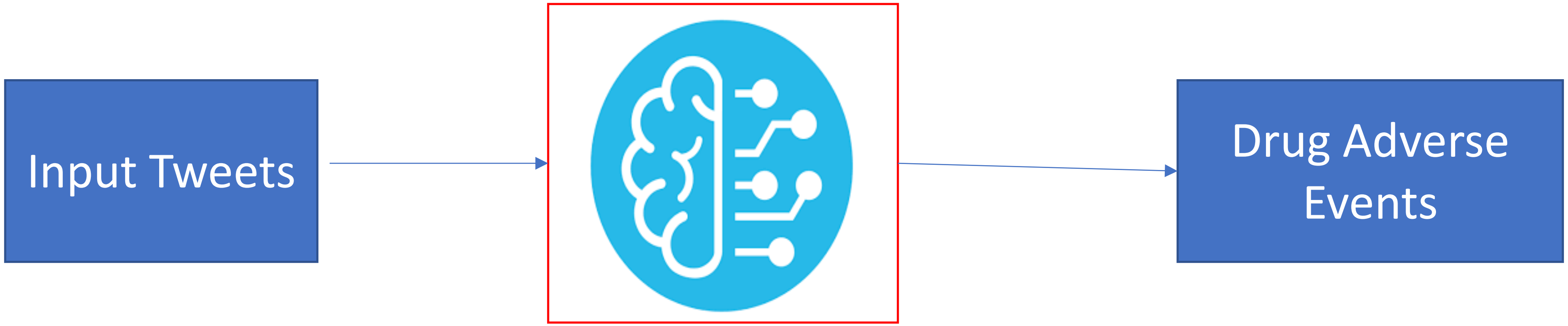
Background

- Large language models (LLM) advantage in processing social media.

  - LLMs are designed to understand human language in a context-aware manner
  - LLMs can process large volumes of text data quickly and efficiently
  - LLMs can be trained or fine-tuned to extract specific information from unstructured text
  - LLMs can help to standardize and normalize the diverse ways that people describe adverse events on social media

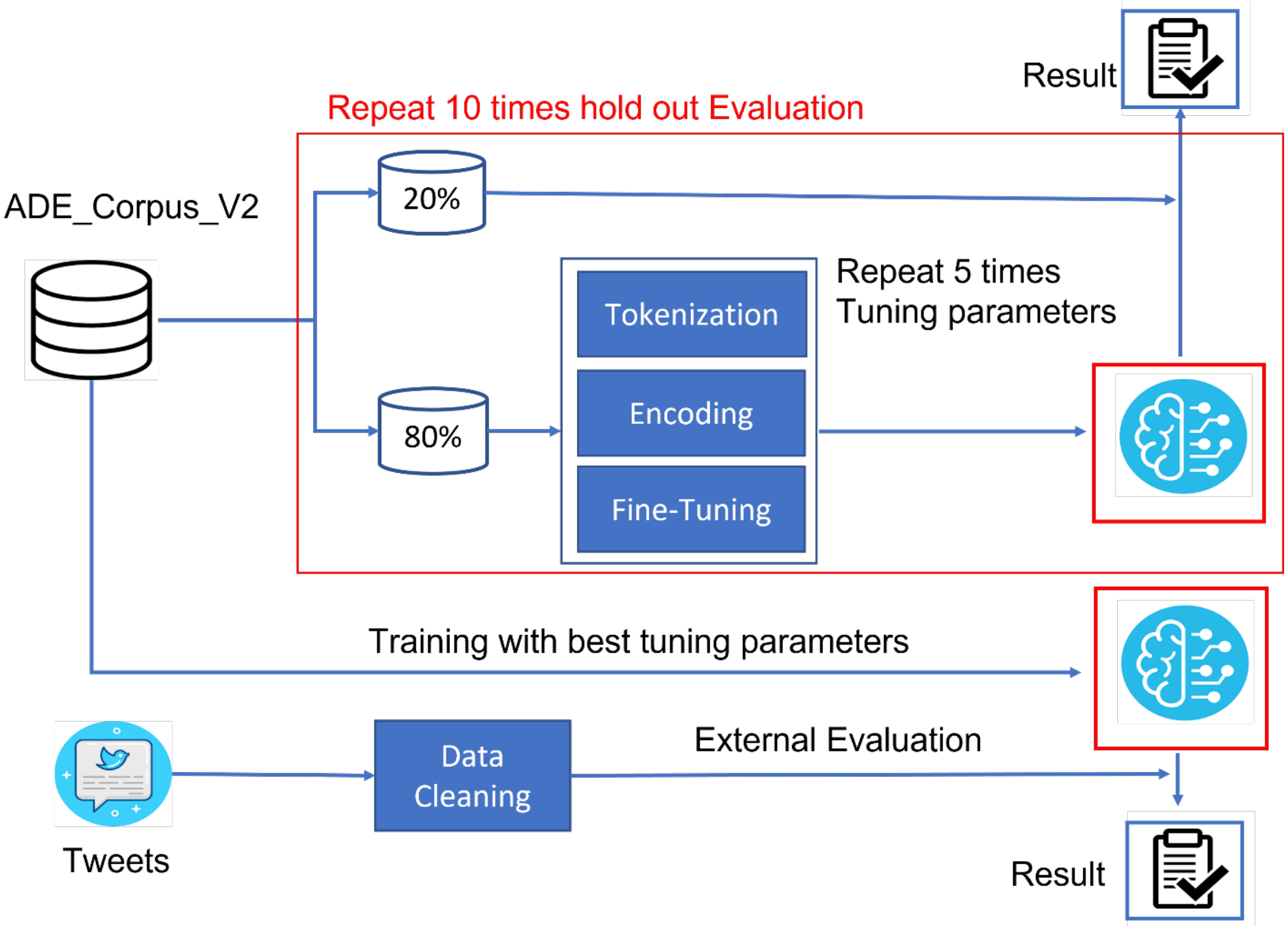
Objective

- To use large language models (LLMs) to extract Adverse event from tweets during covid 19.



Adverse Event Extraction
Large Language Model

Study Design



ADE-Corpus-V2 Dataset

- The ADE-Corpus-V2 (Adverse Drug Event Corpus) is a dataset often used in biomedical natural language processing. It contains sentences extracted from the PubMed database, annotated for mentions of drugs and adverse effects.
- This annotated dataset could help to support supervised learning task for extracting adverse events in document.
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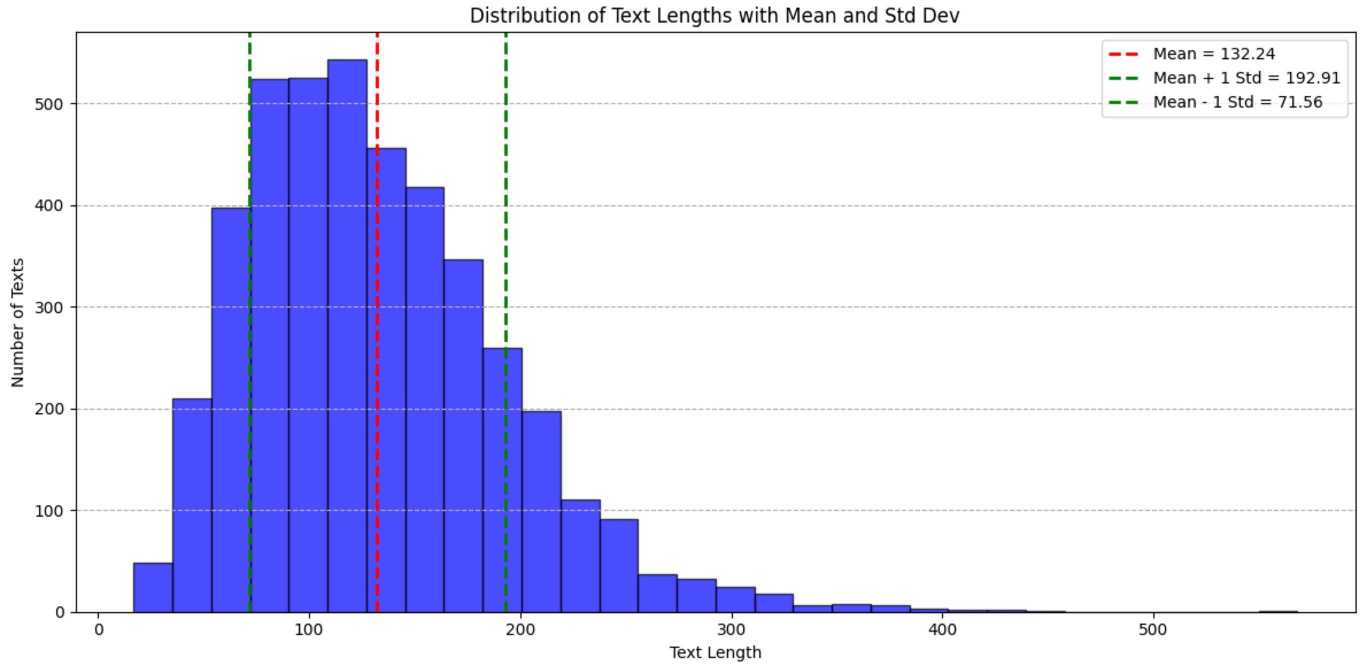


Number of documents	4271
Number of Adverse Events	6821
Distinct Adverse Events	3341

- 3416 documents for training (80%)
- 855 Documents for testing (20%)

Tweet Dataset

- Social Media Mining for Health (SMM4H) dataset.

	A	B
1	Tweet_ID	Text
2	SMM4H2022ykI8vN7jZYnV57AM	@USER__________ i found the humira to fix all my crohn's issues, but cause other issues. i went off it due to issues w nerves/muscle spasms
3	SMM4H2022uCZV2SRsCe4vzjFm	@USER___________ have to go to a doc now to see why i'm still gaining. stupid paxil made me gain like 50 pounds ?? and now i have to lose it
4	SMM4H20229Aha6m4XERqYdFWf	06.30 day 14 Rivaroxaban diary. Thanks to paracetamol and hot water bottle I had 4 hrs continuous sleep. Woke uo with frontal headache, 1/2
5	SMM4H2022UAvDTQWOIacvBkzp	rt @USER________: my philly dr prescribed me trazodone,1pill made me so fkn sick, couldnt move 2day.xtreme migraine, puke, shakes. any1else '
6	SMM4H2022qNHntuJnkevkahGr	ciprofloxacin: how do you expect to sleep when your stomach is a cement mixer?
7	SMM4H2022a2hde3adQrDE2HIV	debating on taking a trazodone and literally passing out for the day.
8	SMM4H2022hceks3meUmDcJLy8	why seroquel can make me put on 20 over kg: it acts like an insulin blocker or something.
9	SMM4H2022Obitap6ILHXjD5SH	@USER_____ thanks :) i so wanted venlafaxine to work cos at least it didn't increase my appetite like citalopram did.
10	SMM4H2022MzDdtDqSq1LhsEKO	So glad I'm off #effexor, so sad it ruined my teeth. #tip Please be carefull w/ taking #antideppresiva and read about it 1st! #venlafaxine

	A	B	C	D
1	Tweet_ID	label	Adverse Event	meddra_pt_id
2	SMM4H2022ykI8vN7jZYnV57AM	ADE	nerves	10029177
3	SMM4H2022ykI8vN7jZYnV57AM	ADE	muscle spasms	10028334
4	SMM4H2022uCZV2SRsCe4vzjFm	ADE	gaining	10047896
5	SMM4H2022uCZV2SRsCe4vzjFm	ADE	gain like 50 pounds	10047896
6	SMM4H20229Aha6m4XERqYdFWf	ADE	frontal headache	10019211
7	SMM4H2022UAvDTQWOIacvBkzp	ADE	sick	10016365
8	SMM4H2022UAvDTQWOIacvBkzp	ADE	migraine	10027599
9	SMM4H2022UAvDTQWOIacvBkzp	ADE	puke	10047700
10	SMM4H2022UAvDTQWOIacvBkzp	ADE	shakes	10040528
11	SMM4H2022qNHntuJnkevkahGr	ADE	sleep	10041017

909 Tweets.

87 Drug Adverse Events extracted.

61 distinct Drug Adverse Event Terms.

Adverse Event Extraction Model Details

➢ Adverse Event Name Entity Recognition

ADE_Corpus_V2

Input

Output

Sentence 1 | I feel like a zombie after taking Advil

AE: feel like a zombie

Name Entity Recognition (NER) :
identifying and classifying named entities (Adverse Events) in text data.
Also be referred to as a special type of Token (word) Classification.

NER_class	Label	Meaning
O	0	Token is not part of named entity (Adverse Event)
B-AE	1	Beginning of named entity (Adverse Event)
I-AE	2	Inside named entity (Adverse Event)

I	feel	like	a	zombie	after	taking	Advil
O	B-AE	I-AE	I-AE	I-AE	O	O	O

Adverse Event Extraction Model Details

Sentence1: I feel like a zombie after taking Advil

AE: feel like a zombie

Tokenization {Padding +Masking}

Token	CLS	I	feel	like	a	zombie	after	taking	Advil	SEP	PAD	...
NER	None	O	B-AE	I-AE	I-AE	I-AE	O	O	O	None	None	None
Label	-100	0	1	2	2	2	0	0	0	-100	-100	-100
Mask	1	1	1	1	1	1	1	1	1	1	0	0

12 Encoder layers from pretrained bert-base-uncased Model

Encoding

	CLS	I	feel	like	a	zombie	after	taking	Advil	SEP	PAD	...
Encoder	[768]	[768]	[768]	[768]	[768]	[768]	[768]	[768]	[768]	[768]	[768]	[768]

Neural Network

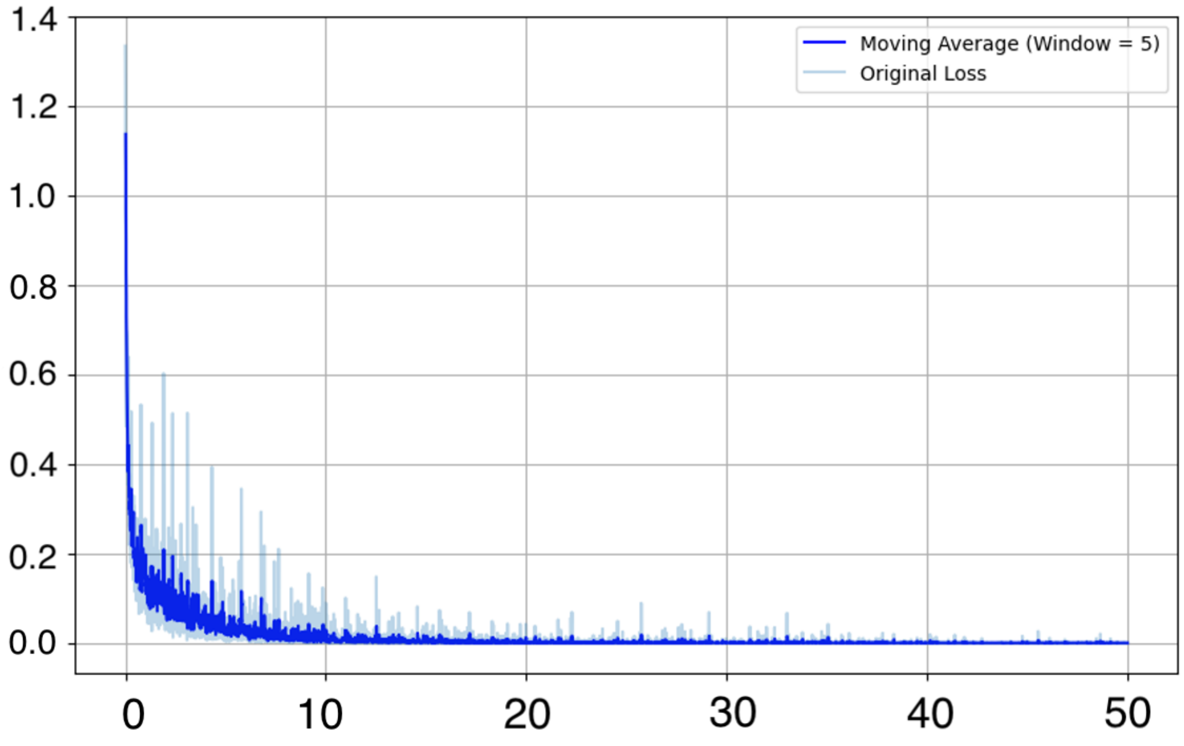
Fine-Tuning

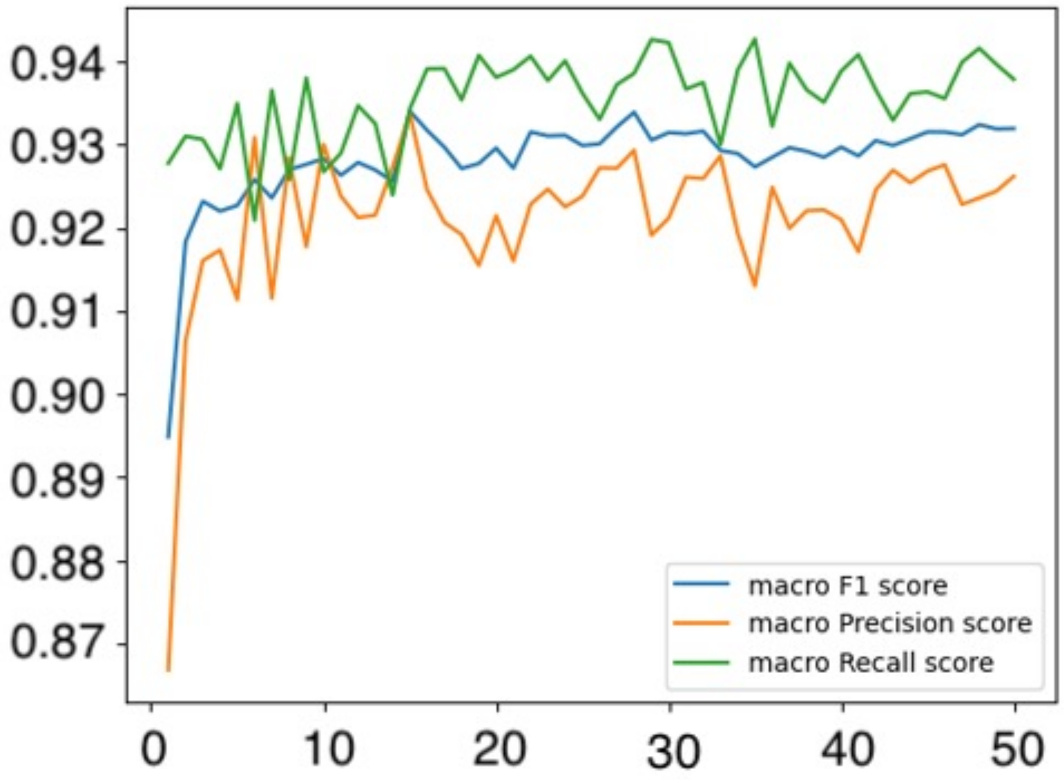
	CLS	I	feel	like	a	zombie	after	taking	Advil	SEP	PAD	...
	[3]	[3]	[3]	[3]	[3]	[3]	[3]	[3]	[3]	[3]	[3]	[3]
Output	-100	0	1	2	2	2	0	0	0	-100	-100	-100

Loss = nn.CrossEntropyLoss (Output, Label)

Adverse Event Extraction Model Fine-tuning

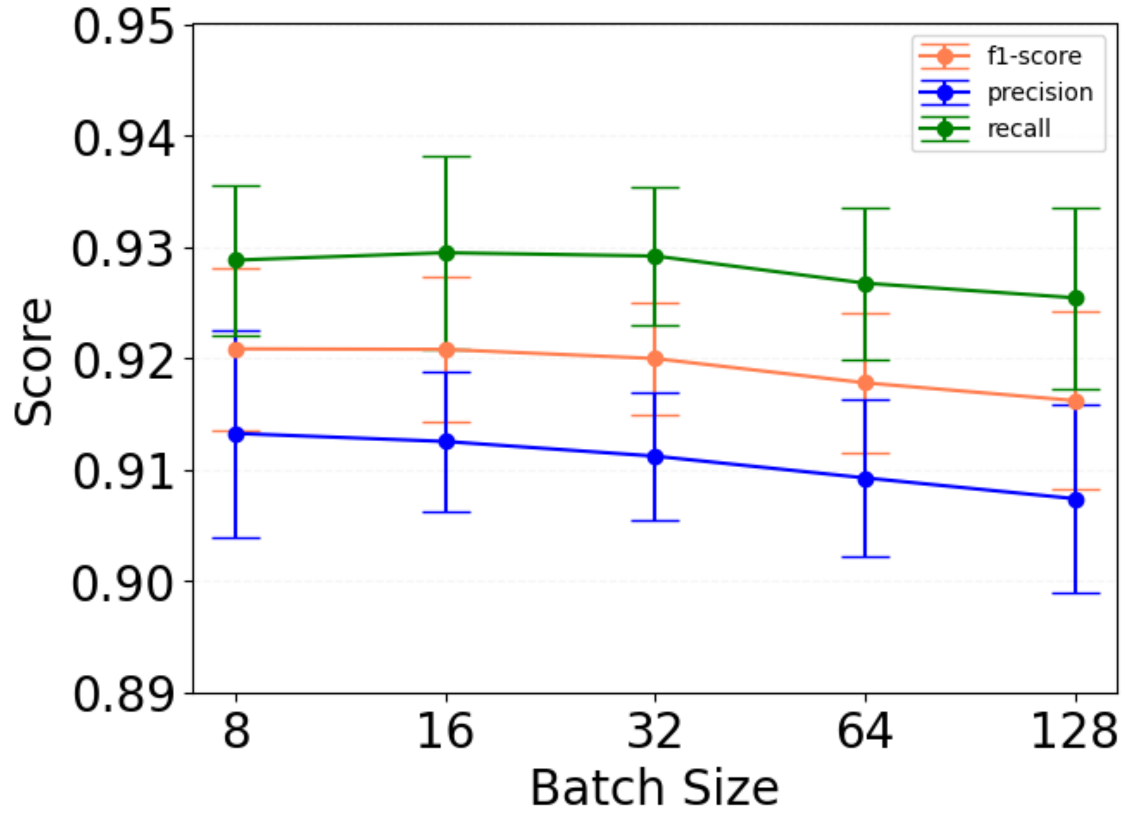
- Epochs fine-tuning

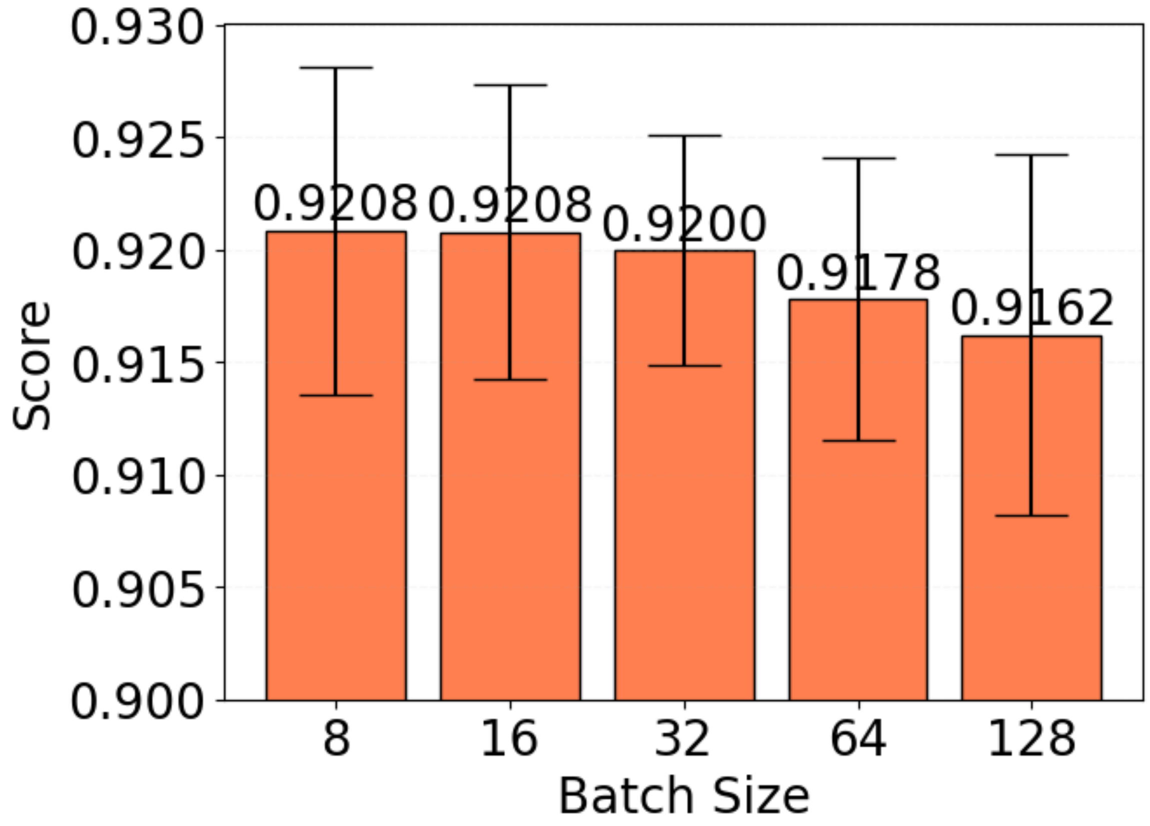




Adverse Event Extraction Model Fine-tuning

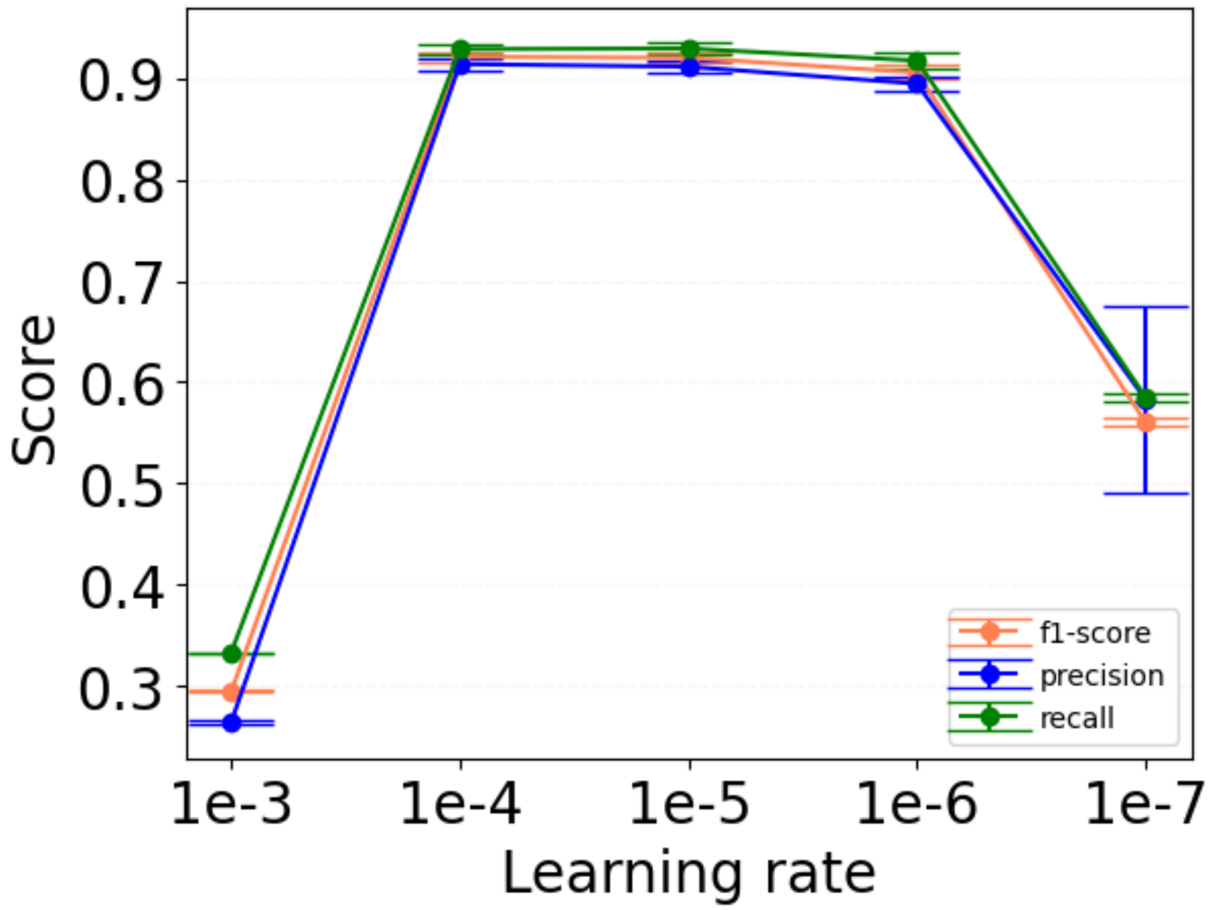
- Batch size fine-tuning

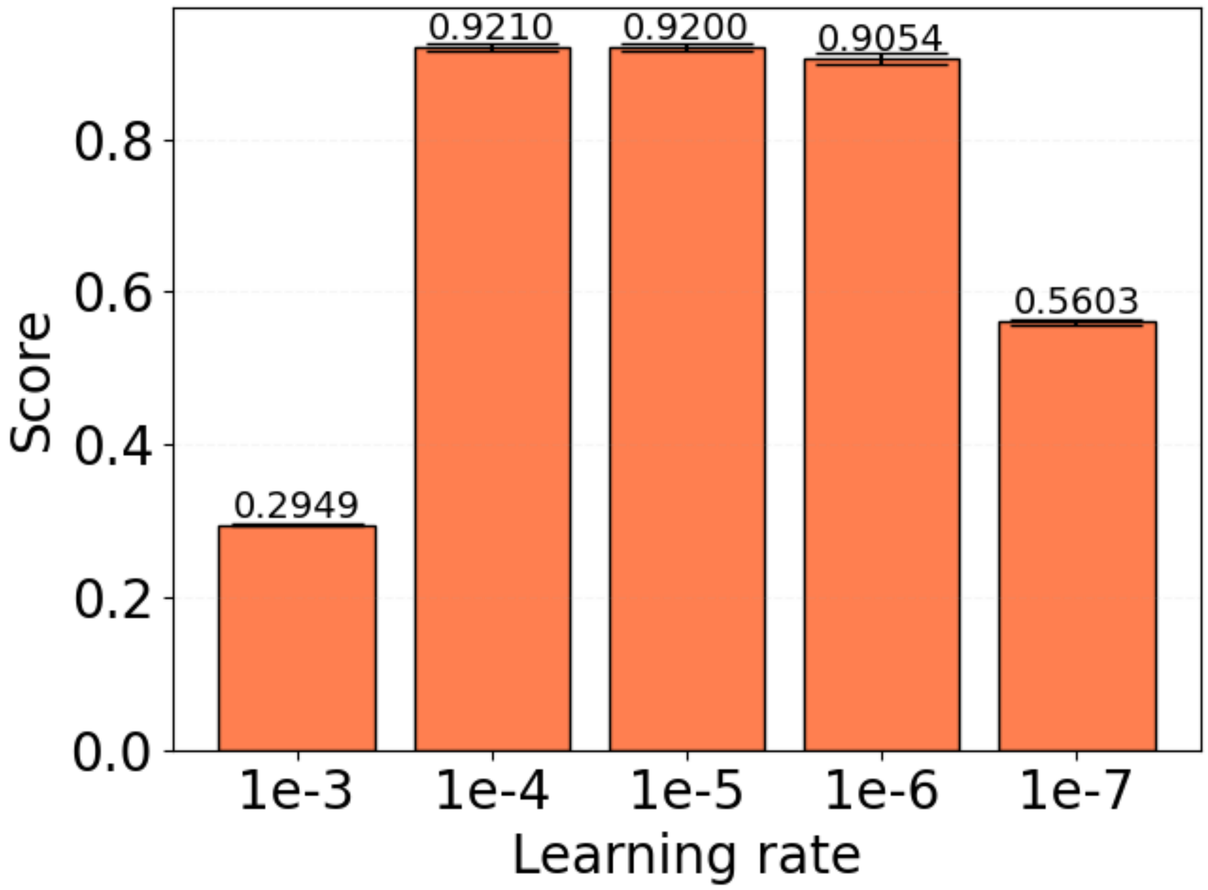




Adverse Event Extraction Model Fine-tuning

- Learning rate fine-tuning





Adverse Event Extraction Model Training

```
model_checkpoint = "bert-base-uncased"
batch_size = 32
args = TrainingArguments(
f"{model_name}-finetuned-{task}",
evaluation_strategy = "epoch",
learning_rate=1e-5,
per_device_train_batch_size=batch_size,
per_device_eval_batch_size=batch_size,
num_train_epochs=50,
)
```

Training model with the best Fine-tuning parameters

Epoch	Training Loss	Validation Loss	Precision	Recall	F1	Accuracy
1	0.118000	0.161656	0.848459	0.905741	0.874921	0.941999
2	0.068400	0.130561	0.891887	0.906182	0.898845	0.954261
3	0.324000	0.138889	0.882235	0.915155	0.897995	0.952956
4	0.326700	0.138463	0.889154	0.920435	0.904192	0.955101
5	0.026300	0.142402	0.888742	0.919310	0.903448	0.955007

```
TrainOutput(global_step=855, training_loss=0.1346952303067634, metrics={'train_runtime': 75.1936, 'train_samples_per_secon
d': 181.664, 'train_steps_per_second': 11.371, 'total_flos': 438057766181016.0, 'train_loss': 0.1346952303067634, 'epoch':
5.0})
```

Evaluation Metrics

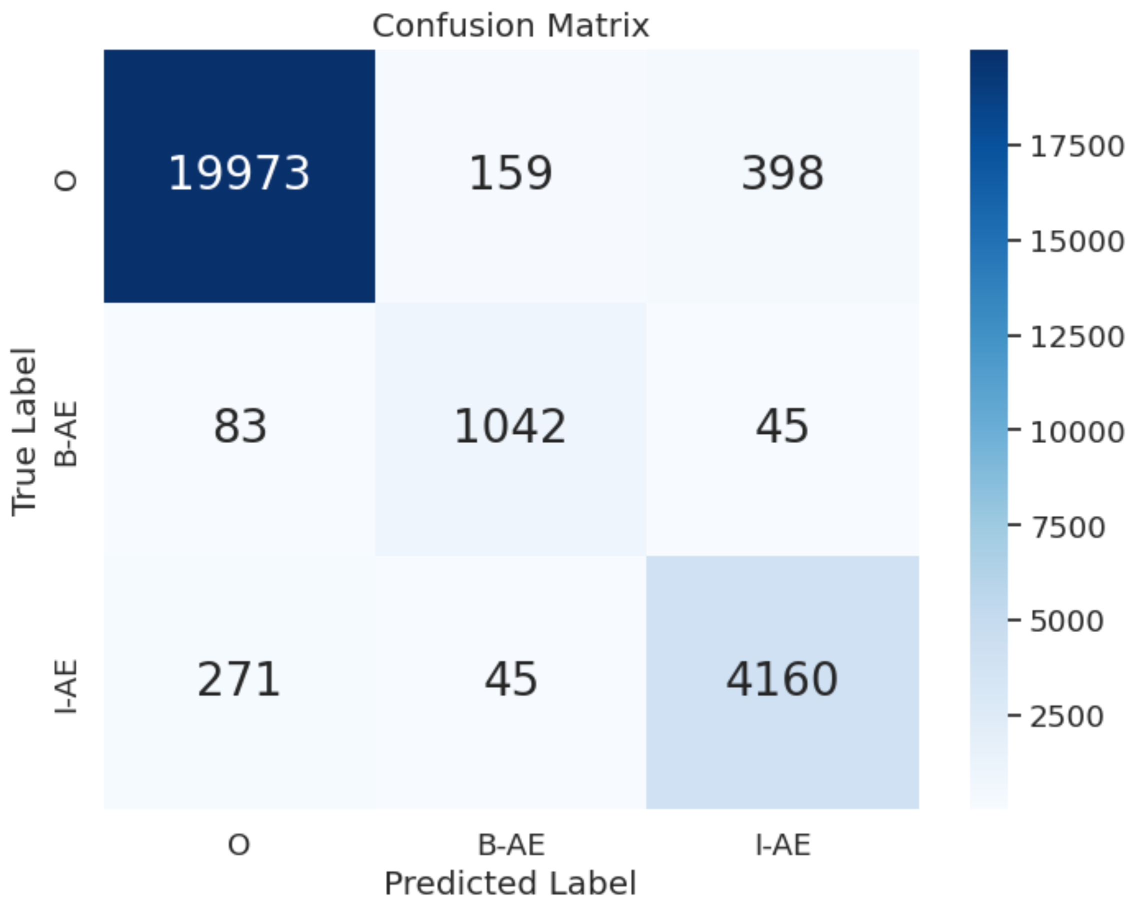
$$Precision_i = \frac{TP_i}{TP_i + FP_i} \quad (1)$$

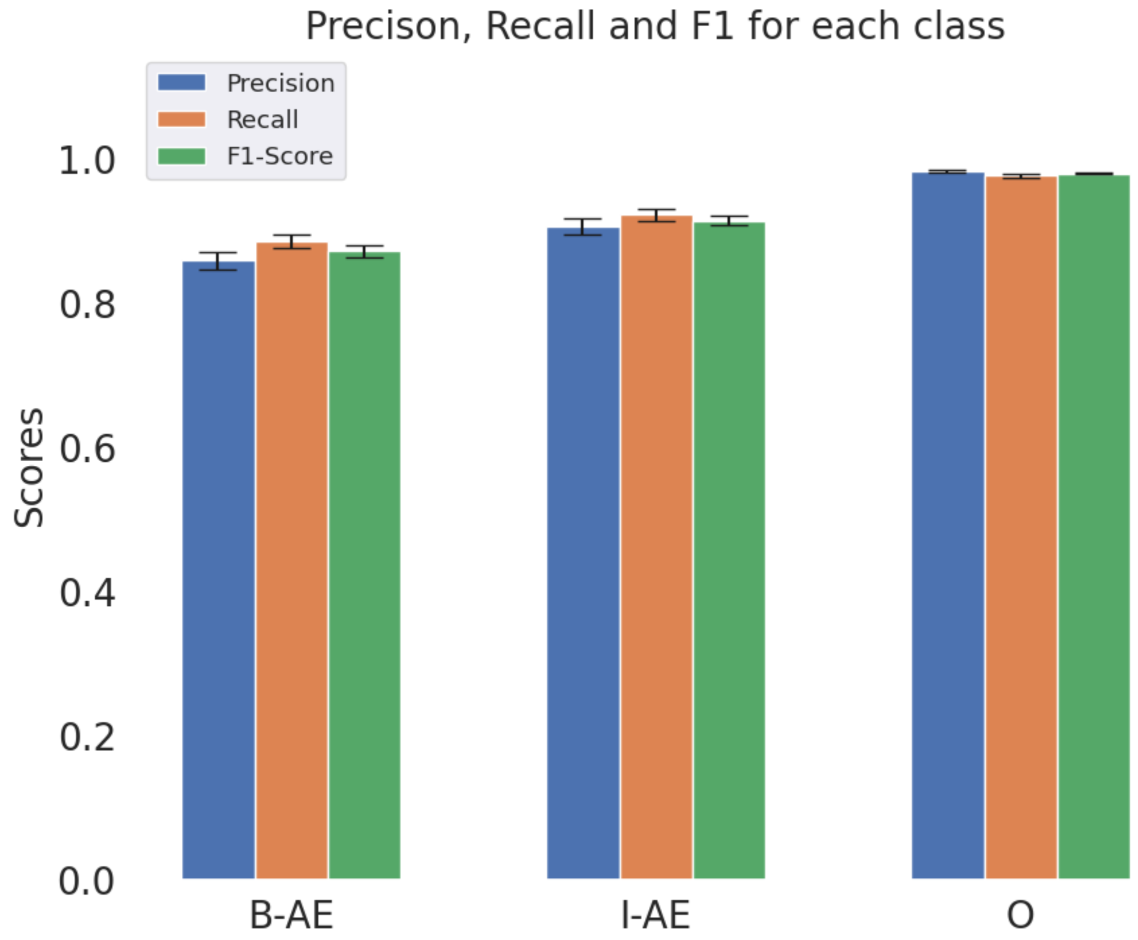
$$Recall_i = \frac{TP_i}{TP_i + FN_i} \quad (2)$$

$$F1_i = 2 * \frac{Precision_i * Recall_i}{Precision_i + Recall_i} \quad (3)$$

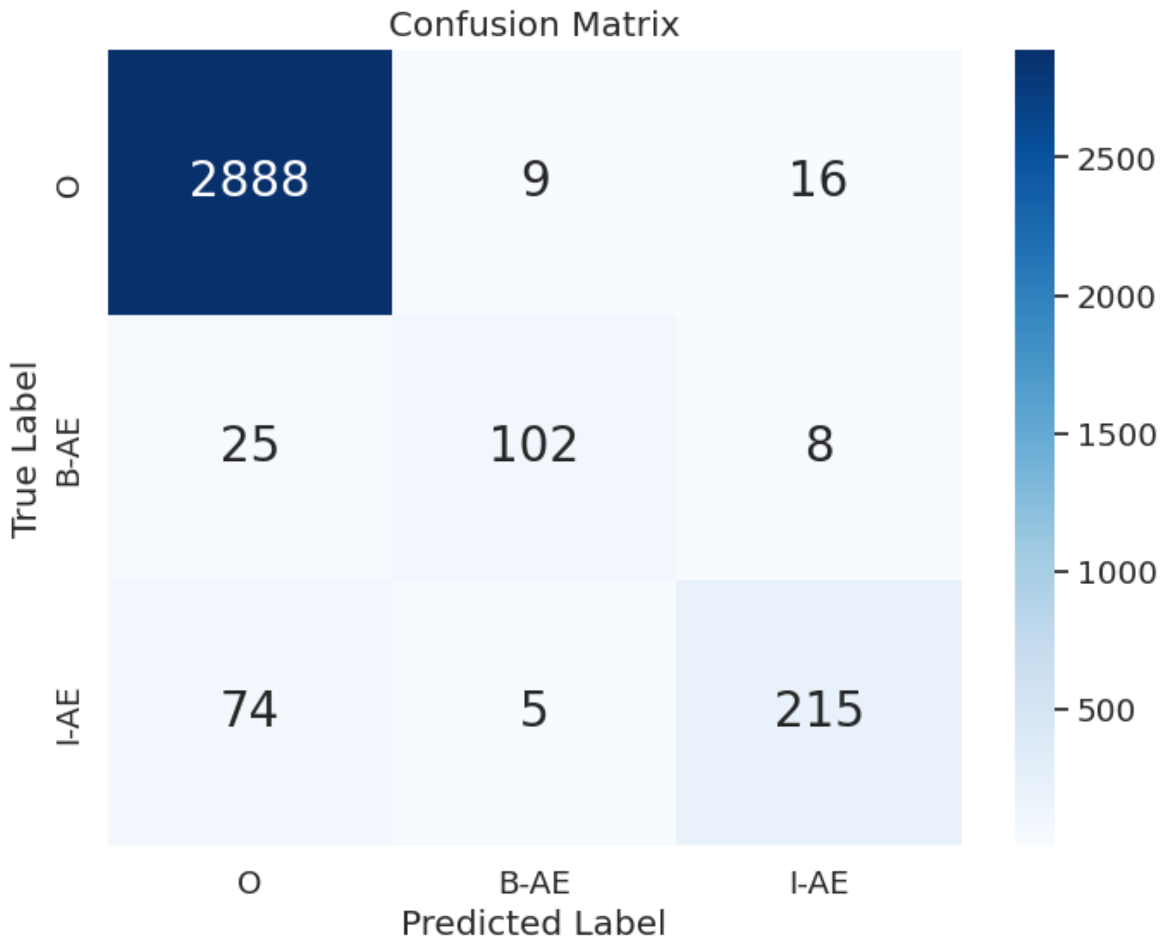
TP: True Positive
FP : False Positive
FN : False Negative

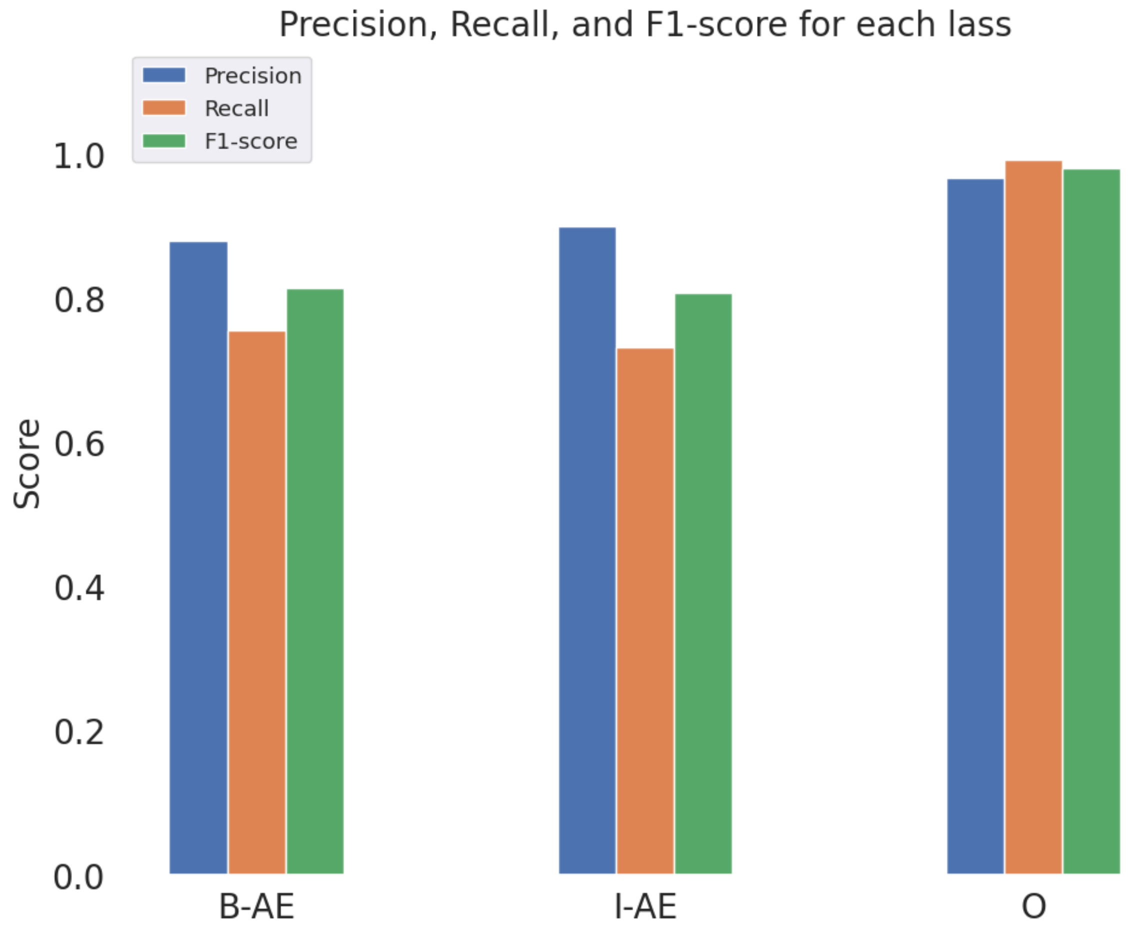
10 times hold out Internal Evaluation on ADE-Corpus-V2





External Evaluation Result on SMM4H





Case study for External Evaluation on SMM4H

Case	AE terms extraction example in Tweets Data
exactly recognized AE	06.30 day 14 Rivaroxaban diary. Thanks to paracetamol and hot water bottle I had 4 hrs continuous sleep. Woke uo with ***frontal headache***, 1 2
miss recognized AE	rt my philly dr prescribed me trazodone,1pill made me so fkn ***sick***, couldnt move 2day.xtreme ***migraine, puke, shakes***. any1else
partially recognized AE	well i'm taking it with a mood stabilizer (lamictal). i can't take anti-depressants by themselves-***triggers my rapid cycling***
recognized more than AE	does cipro make anyone's else's ***brain turn to mush*** or am i actually just going crazy?

Summary

- Our research underscores the significance of social media platforms as valuable resources for monitoring health-related information and adverse events associated with medications and treatments in drug safety surveillance.
- Our study not only highlights the efficacy of BERT-based language models in identifying drug adverse events in the dynamic landscape of social media data but also emphasizes the importance of a comprehensive implementation study design and evaluation.
- Leveraging publicly available labeled adverse event data from the ADE-Corpus-V2, we optimized key hyperparameters during model construction. Through ten hold-out evaluations on ADE-Corpus-V2 data and external validation using human-labeled adverse event tweets data from SMM4H, our model consistently demonstrated high accuracy in drug adverse event detection.
- Our research contributes to advancing pharmacovigilance practices and methodologies, particularly in the context of emerging information sources like social media.

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