

# Document Classification for COVID-19 Literature

Bernal Jiménez Gutiérrez, Juncheng Zeng, Dongdong Zhang, Ping Zhang, Yu Su

The Ohio State University

{jimenezgutierrez.1, zeng.671, zhang.11069, zhang.10631, su.809}@osu.edu

The global pandemic has made it more important than ever to quickly and accurately retrieve relevant scientific literature for effective consumption by researchers in a wide range of fields. We provide an analysis of several multi-label document classification models on the LitCovid dataset, a growing collection of 23,000 research papers regarding the novel 2019 coronavirus. Additionally, we test these models on a subset of the CORD-19 dataset containing 100 papers about previous epidemics we manually annotated.

Class	LitCovid	CORD-19 Set
Prevention	11,042	12
Treatment	6,897	20
Diagnosis	4,754	25
Mechanism	3,549	70
Case Report	1,914	2
Transmission	1,065	6
General	368	7
Forecasting	461	2

Table 1: Category distribution for the *LitCovid* and *CORD-19 Test Datasets*.

We find that pre-trained language models fine-tuned on this dataset outperform all other baselines and that BioBERT surpasses the others by a small margin with micro-F1 and accuracy scores of around 86% and 75% respectively.

Model	Dev Set		Test Set	
	Acc.	F1	Acc.	F1
LR	68.5	81.4	68.6	81.4
SVM	71.2	83.4	70.7	83.3
LSTM	69.0 ± 0.9	83.9 ± 0.1	68.9 ± 0.3	83.2 ± 0.2
LSTM <sub>reg</sub>	71.2 ± 0.5	83.9 ± 0.3	70.8 ± 0.7	83.6 ± 0.5
KimCNN	69.9 ± 0.2	83.3 ± 0.3	68.8 ± 0.1	82.7 ± 0.1
XML-CNN	72.9 ± 0.4	84.1 ± 0.2	71.7 ± 0.7	83.5 ± 0.3
BERT <sub>base</sub>	74.3 ± 0.6	85.5 ± 0.4	73.6 ± 1.0	85.1 ± 0.5
BERT <sub>large</sub>	75.1 ± 3.9	85.9 ± 1.9	74.4 ± 2.7	85.3 ± 1.4
Longformer	74.4 ± 0.8	85.6 ± 0.5	73.9 ± 0.8	85.5 ± 0.5
BioBERT	75.0 ± 0.5	86.3 ± 0.2	75.2 ± 0.7	86.2 ± 0.6

Table 2: Performance for each model expressed as *mean ± standard deviation* across three training runs.

We evaluate the data efficiency and generalizability of these models as essential features of any

system prepared to deal with an urgent situation like the current health crisis.

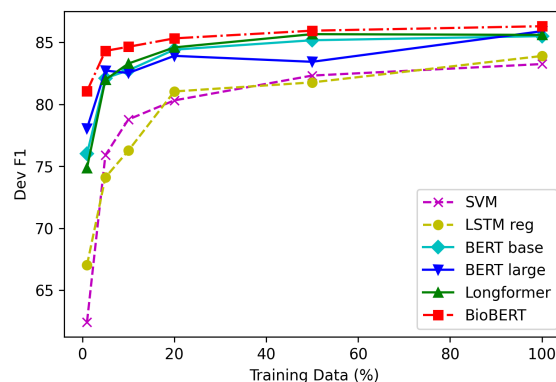


Figure 1: Data efficiency analysis.

All pre-trained language models tested are impressively data efficient, with BioBERT achieving an F1 score only 4 points below its maximum score using only 1% of the training data.

	Acc.	F1
SVM	29.0	62.8
LSTM <sub>reg</sub>	32.7 ± 1.5	67.7 ± 0.7
Longformer	41.3 ± 6.4	70.0 ± 2.9
BioBERT	36.0 ± 7.8	69.7 ± 2.8

Table 3: Performance on the CORD-19 Test Set expressed as *mean ± standard deviation* across three training runs.

From Table 3, we can see that performance drops significantly on the CORD-19 test set which does not mention COVID-19. This shows that more work needs to be done for these models to be immediately useful in future health emergencies.

Finally, we explore 50 errors made by the best performing models on LitCovid documents and find that they often (1) correlate certain labels too closely together and (2) fail to focus on discriminative sections of the articles; both of which are important issues to address in future work. Both data and code are available on GitHub <sup>1</sup>.

<sup>1</sup><https://github.com/dki-lab/covid19-classification>

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