Classifying COVID-19 vaccine narratives

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Abstract

COVID-19 vaccine hesitancy is widespread, despite governments' information campaigns and WHO efforts. One of the reasons behind this is vaccine disinformation which widely spreads in social media. In particular, recent surveys have established that vaccine disinformation is impacting negatively citizen trust in COVID-19 vaccination. At the same time, fact-checkers are struggling with detecting and tracking of vaccine disinformation, due to the large scale of social media.

To assist fact-checkers in monitoring vaccine narratives online, this paper studies a new vaccine narrative classification task, which categorises COVID-19 vaccine claims into one of seven categories. Following a data augmentation approach, we first construct a novel dataset for this new classification task, focusing on the minority classes. We also make use of fact-checker annotated data. The paper also presents a neural vaccine narrative classifier that achieves an accuracy of 84% under cross-validation. The classifier is publicly available for researchers and journalists.

Introduction

Vaccination is one of the most effective public health interventions, but it is essential that immunization programs are able to achieve and sustain high vaccine uptake rates. Overcoming vaccine hesitancy, which refers to delay in uptake or refusal of vaccines, is a major challenge [1] and the WHO has named it one of the ten threats to global health in 2019 [2]. Vaccine hesitancy is a complex and context specific phenomenon, varying across time, place and even vaccines [3]. It could be caused by various factors such as concerns about side effects, costs, and misinformation.

Therefore, detecting and tracking COVID-19 vaccination misinformation and the ability to monitor effectively the wider public social media debates around vaccination and vaccine hesitancy is both urgent and timely, and of high importance to national governments and society as a whole.

Although social media platforms like Twitter, Facebook, and YouTube have taken actions to limit the spread of misinformation, simply identifying and removing misinformation from platforms is not enough, as the concerns of the vaccine-hesitant citizens also need to be monitored and responded to. Consequently, fact-checkers and other professionals need analytical tools that help them better monitor misinformation, vaccine hesitancy, vaccine-related debates and narratives.

Topic analysis of narratives about vaccines could be used for this purpose, however, a large manual effort is required, due to the lack of a vaccine-related topic classifier. For example, Smith et al [4] gather over 14 million vaccine-related posts from Twitter,

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Instagram, and Facebook to research vaccine-related narratives. The posts are categorized into six topics based on a novel typology designed to capture the ways narratives are framed. However, manual analysis was feasible on only a small sample of 1,200 posts, which, given the small scales, leaves significant gaps in the understanding and tackling vaccine hesitancy.

Guided by these needs, the novel contributions of this paper are in:

- 1. Proposing a new seven-way classification task and dataset for categorising vaccine related online narratives. The classification task adopts the six categories (see Table 1) defined in [4]. The dataset is built based on manual annotation and data augmentation. Our experiment demonstrates that the augmented data significantly boosts classifier performance.
- 2. Building and making available a vaccine narrative classifier, based on the Classification Aware Neural Topic Model (CANTM) [5]. CANTM originally achieved state-of-the-art performance in COVID-19 misinformation classification [5] and is particularly suited to vaccine narrative classification too, as it is robust on small training sets. For reproducibility, the classifier is publicly available as a web service

(https://cloud.gate.ac.uk/shopfront/displayItem/covid19-vaccine).

Table 1. Description and examples of each topic

Topic	Description	Examples
Conspiracy (Cons)	Known or novel conspiracies and	Bill Gates: We need to depopulate the planet.
	conspiracy theories involving vac-	Also Bill Gates: Save your life with my vaccine.
	cines or their development	
Development, Pro-	The ongoing progress or chal-	World's first COVID-19 vaccine! Russia's
vision and Access	lenges concerning the develop-	Sechenov University completes clinical trials
(DPA)	ment, testing and provision of	of Coronavirus vaccine.
	vaccines as well as the access to	
	vaccines	
Liberty/Freedom	Civil liberties and personal free-	States have authority to fine or jail people who
(LF)	dom considerations surrounding	refuse coronavirus vaccine, attorney says.
	vaccines and vaccination policies	
Morality, Religios-	Moral, ethical and religious con-	Kanye West Praises Trump, Hammers Planned
ity and Ethics (MRE)	cerns around vaccines	Parenthood, Likens COVID Vaccine To 'Mark
		Of The Beast'.
Politics and Eco-	Political, economic or business de-	The Democrats are just ANGRY that the vac-
nomics (PE)	velopments related to vaccines	cine and delivery are so far ahead of schedule.
		They hate what they are seeing. Saving lives
		should make them happy, not sad!
Safety, Efficacy and	Safety and efficacy of vaccines,	The COVID-19 death rate without a vaccine
Necessity (SEN)	including the perceived necessity	is lower than the flu death rate with a vaccine.
	of vaccines	

Related Work

Since the outbreak of the COVID-19 pandemic and accompanying infodemic, large-scale monolingual and multilingual datasets have been collected from different social media platforms in order to intervene and combat the spreading of COVID-19-related disinformation [6–10], with vaccine being a commonly included topic in these datasets.

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As the importance of understanding and tackling COVID-19 vaccination hesitancy grew, increasing efforts have been made to analyse vaccine narratives and discourses, dissemination of false claims and anti-vaccine groups on social media, resulting in the construction of a number of COVID-19 vaccine-focused datasets, without [11,12] or with annotations about veracity (e.g., true or false information) [13], sentiment (e.g., positive, negative or neutral) [14], stance (e.g., pro- or anti-vaccine) [15,16] or topic category (e.g., vaccine development or side effects) [4,17]. The datasets, consequently, can be used to facilitate the research on COVID-19 vaccine-related online information from different aspects, including fact-checking, sentiment analysis, stance detection, and topic analysis.

Topics or themes discussed in the vaccine-related narratives and online debates are an essential dimension. State-of-the-art methods for automatic topic analysis fall typically under one of these categories: topic modelling [18–21], clustering [11,12,16,22], and inductive analysis [4,17]. Topic modelling, represented by Latent Dirichlet Allocation (LDA) [23], is the most commonly used approach at present [18–21]. Clustering methods for topic discovery have been applied to text representations [4,22] or networks [11,12]. For instance, K-means [24] has been used to cluster the average word embeddings of vaccine narratives [22] or to test a human-derived topic typology [4]. After constructing a co-occurrence topic network with hashtags as nodes, the Louvain method [25] is used to extract clustering from the graph [11,12]. The above methods are unsupervised, resulting in no control on the model generation. Therefore, extra work is normally involved in discovering and labelling the topics.

In contrast, inductive analysis relies on experts to analyse the raw textual data and derive topics or themes [4,17,26]. For instance, Bonnevie et al [17] categorise anti-vaccine tweets into twelve conversation themes, such as negative health impacts, pharmaceutical industry and religion. Hughe et al [26] identify twenty-two narrative tropes (e.g., corrupt elites and vaccine injury) and sixteen rhetorical strategies (e.g., brave truthteller and appropriating feminism) in anti-vaccine and COVID-denialist social media posts.

Besides the above work specific to anti-vaccine contents, general COVID-19 vaccine narratives on social media were categorised by fact-checkers and researchers at Frist Draft [4] as belonging to one of six topics, as shown in Table 1.

A potential drawback of inductive analyses is that the amount of data that can be analysed by the human experts is significantly smaller than the volumes analysed through the automatic topic modelling and clustering methods. To overcome this problem, Bonnevie et al create a list of unique keywords for each theme during inductive analysis, which are then used to automatically categorise more posts based on keyword matching [17].

In this paper, we explore machine learning and deep learning methods for automatic vaccine narrative classification according to topics proposed by Smith et al [4].

To the best of our knowledge, this is the first paper to frame online vaccine narrative categorisation as a classification task. In that respect, there are two closely relevant studies. Song et al [5] collect English debunks about COVID-19 and annotate them with ten disinformation categories. They also propose a novel framework that combines classification and topic modelling. Similarly, Shahi et al [8] scrape multilingual COVID-19 related fact-check articles and manually classify them into eleven topics, but the models they explore are limited to veracity prediction. Both papers study disinformation regarding COVID-19, with vaccine covered as only one monolithic category (vaccines, medical treatments, and tests [5] or prevention & treatments [8]). However, our work is vaccine-focused, aiming at finer-grained, automatic categorisation of vaccine narratives.

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Vaccine Narrative Categorisation: Task Definition and Dataset Construction

Definition

We define the COVID-19 vaccine narrative categorisation task as assigning COVID-19 vaccine-related claims to one of the six target topics identified by Smith et al [4]: (1) Cons for vaccine-related conspiracies; (2) DPA for development, provision, and access to vaccination; (3) LF for vaccine-related civil liberties and freedom of choice; (4) MRE for moral, religious, and ethical concerns; (5) PE for political, economic, or business aspects; and (6) SEN for safety and efficacy concerns.

More detailed definitions and examples of the six topics are shown in Table 1. In addition, we introduce a new, seventh category that encompasses claims related to animal vaccines (AnimalVac). The motivation is to recognise or filter out animal vaccine-related posts, which are also captured by keyword-based data collection methods that are typically used for collecting vaccine-related social media posts (e.g., using keywords such as vaccine or vaccines).

Thus, this paper regards the vaccine narrative categorisation task as a seven-way classification problem, with six topics pertaining to COVID-19 human vaccination and one additional topic for animal vaccination.

Dataset Construction

FD data: First Draft researchers and journalists (FD data) collected and annotated manually a number of posts in English with the six human vaccine related topics by [4]. The data is gathered from multiple online platforms (news media, Twitter, Facebook, and Instagram), consisting of texts, images, and videos.

For our experiments all duplicates were removed, together with posts having just video content, since our aim is text-based classification. Posts with images are classified on the basis of their textual content if available and the alternative/alt texts (a short written description of an image, which describes that image for accessibility reasons) accompanying the images.

Table 2 shows the topic distribution of the English FD dataset after data filtering is applied.

Table 2. Distribution of data between classes before and after data augmentation

	Cons	DPA	LF	MRE	PE	SEN	AnimalVac	Total
FD data	26(6%)	116(27%)	37(9%)	7(2%)	108(25%)	134(31%)	0(0%)	428
Augmented	107(13%)	116(14%)	93(12%)	151(19%)	108(13%)	134(17%)	96 (12%)	805

Data Augmentation: As shown in Table 2, the FD dataset is highly imbalanced. Cons, LF, and MRE are minority classes, which only contain 6%, 9%, and 2% of the total posts, respectively. Besides, the FD dataset does not contact posts pertaining to animal vaccines, as these were excluded during their manual analysis.

To address these issues, we perform data augmentation, which includes the collection of new posts for the AnimalVac class, as well as gathering more examples for the three under-represented categories.

Using the Twitter API, we collected posts with vaccine-related hashtags such as #covidvaccine, #AstraZeneca, #vaccines. These tweets are then filtered on the basis of class-specific keywords and hashtags which we identified manually for each target class. As we aim to limit the overlap between the FD dataset and our newly collected data, we

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derived the keywords and hashtags on the basis of the FD codebook, i.e. annotator guidelines:

- 1. Cons: known conspiracy theories are considered, such as QAnon, ID2020, nanorobots insertion, new world order, and deep state. In addition, we included two other conspiracies fact-checked by IFCN (https://www.poynter.org/coronavirusfactsalliance/), but not captured in the FD data: (a) The body can receive 5G signal after the vaccine is taken; and (b) China is collecting human DNA from all over the world through its vaccines in order to create a biological weapon.
- 2. LF: hashtags and terms regarding mandatory vaccination (e.g., #MandatoryVaccine, #NoJabNoPay), and concepts suggesting that mandatory vaccine programs undermine personal liberty or constitute a medical dictatorship (e.g., #MedicalFreedom, #InformedConsent, #MyBodyMyChoice).
- 3. MRE: keywords about how people are being used as animals in vaccine testing (e.g., lab rats, guinea pigs), and about religion or ideological stance in opposition to vaccines (e.g., aborted fetuses, changing DNA).
- 4. AnimalVac: hashtags such as #animalhealth, #WorldAnimalVaccinationDay, and #petmedicine are utilized to find the target tweets. As the number of the matched tweets is relatively small, we also collect Facebook posts to balance the dataset. They are pick out if they contain certain names of animal diseases and the word "vaccine".

The full list of keywords and hashtags per class are shown with examples in Table 3.

All posts matching the keywords and hashtags for each target class are then manually annotated by the authors, in order to ensure label quality. Table 2 presents also the new data distribution following this augmentation. The proportion of Cons, LF and MRE has increased to 13%, 12%, and 19% respectively and 96 posts related to animal vaccines are also included.

Predictive Model

Our experiments are based on the CANTM model which achieves state-of-the-art performance on COVID-19 disinformation categorisation [5]. It combines classification and topic modelling under a stacked asymmetric variational autoencoder framework, consisting of six main sub-modules (represented in six different colors in Fig 1):

- 1. M1 encoder (or M1 inference network) q(z|x) yellow
- 2. M1 decoder (or M1 generation network) $p(x_{bow}|z)$ pink
- 3. M1 Classifier $\hat{y} = f(z)$ orange
- 4. M1 Classifier decoder $p(x_{bow}|\hat{y})$ green
- 5. M2 encoder (or M2 inference network) $q(z_s|x,\hat{y})$ blue
- 6. M2 decoder (or M2 generation network) $p(x_{bow}|\hat{y}, z_s)$ and $p(\hat{y}|z_s)$ purple

The advantages of adopting the CANTM are as follows:

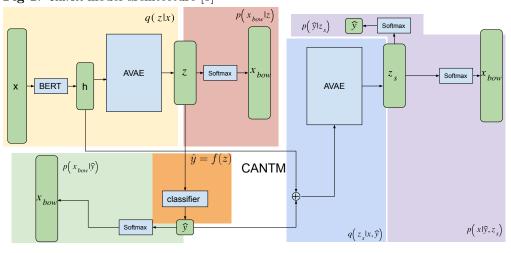
1. It has **robust classification performance** especially on small training sets, such as ours. The model first encodes the input text using the pre-trained language model Bidirectional Encoder Representations from Transformers (BERT) [27] that transforms the input into a BERT-enriched feature representation

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Table 3. Keywords and hashtags for data augmentation.

Class	Keywords/hashtags	Examples
Cons	QAnon, new world order, nano,	(1) Vaccination day. When the time comes, get vaccinated.
	ID2020, deep state, China	No one will microchip you like a cat and 5G will not control
	weapon, China DNA, 5g	your mind.
		(2) Filled with nano particles to alter our DNA! The Mod-
		erna vaccine is the Gates vaccine.
LF	#freedom, #liberty, #NoVac-	(1) Before you all start, this is NOT about Pro #Vaccina-
	cineForMe, #MyBodyMyChoice,	tion or those against. This is about how the #nojabnopay
	#InformedConsent, #Mandato-	discriminates against free choice and the rich/poor.
	ryVaccine, #MedicalFreedom,	(2) This is how I feel!!! We should have all of our rights and
	#NoJabNoPay, medical dictator-	freedoms to choose what is best for us. #freedom #our-
	ship, mandatory	bodyourchoice #NoVaccineForMe #novaccinepassport.
MRE	fetal/fetus/fetuses, Mark of the	(1) Vatican says use of Covid vaccines made from aborted
	beast, guinea pig(s), lab rat(s),	fetal tissue is ethical.
	DNA, mRNA, medical ethics	(2) Africans let's rise up and put an end to this menace
		We are not lab rats!! We are not test tubes!! #Nomorevac-
		cinetesting
AnimalVac	#animalhealth, #animalwelfare,	(1) Will Your Pet Need a COVID-19 Vaccine? #covid19
	#WorldAnimalVaccinationDay,	#AnimalHealth
	#petmedicine, #vetmedicine,	(2) Outbreaks of disease are unpredictable and can have a
	Feline Panleukopenia, Feline	major financial impact on your farm business. Vaccination
	Herpesvirus, Feline Calicivirus,	is a planned approach to help to protect your livestock and
	Feline Leukaemia Virus, Ca-	improve animal health $\#VaccinesWork\ \#WorldAnimalVac-$
	nine Distemper Virus, Canine	cinationDay
	Parvovirus, Canine Adenovirus,	
	Canine Rabies	

Fig 1. CANTM model architecture [5]



h. The latent topic z is generated from a random node in a variational autoencoder (VAE) based on the enriched feature representation h. The classifier is trained on the random generated latent topic from the VAE. In this case the classifier has never seen the 'real' training data during training time, thus reducing over-fitting likelihood.

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- 2. CANTM provides classification explanations. Explanations help users to understand the rationale for the model's decisions, and allow them to assess the biases and risks in applying the CANTM model on unseen data set. It provides explanation in four different dimensions, 1) Word-level attention score from BERT model; 2) Classification-regularised topics z; 3) Classification-aware topics z; and 4) Class-associated topic words $p(x_{bow}|\hat{y},z_s)$. Explanations 1, 2 and 3 are local explanations, that provide an explanation on each input instance. Explanation 4 (Class-associated topic words) is global, as it provides model-level explainability.
- 3. The derived **topics** are associated with the target classes. Different to unsupervised topics models, the CANTM model is jointly training the topic model and the classifier. Consequently, the generated topics are directly related to the given target classes, rather than randomly generated.

In addition to the original CANTM model, we also experiment with a new variant – CANTM-COVID – where we replace BERT by COVID-Twitter-BERT [28] that is pretrained on COVID-19 related tweets based on BERT-large [27].

Experimental Setup

Baselines

In order to contextualise the performance of the two CANTM models, we also trained the following baseline models:

- 1. BOW-LR: We train a Logistic Regression model with bag-of-words using L2 regularization, using the scikit-learn implementation [29].
- 2. Sparse Contextual Hidden and Observed Language AutoencodeR (SCHOLAR) [30]: SCHOLAR adopts VAE and directly inserts label information in the encoder during training in order to generate latent variable dependent on the labels. Zero vectors are used to represent the labels in the test set during inference. We use the author's implementation of SCHOLAR (https://github.com/dallascard/scholar).
- 3. BERT [27] and BERT-COVID [28]: We fine-tune bert-base-uncased [27] and COVID-Twitter-BERT [28] model implemented on Hugging Face [31] and follow the suggestion by Song et al [5] to enable a fair comparison between BERT and CANTM: an additional 500 dimensional feed-forward network is built on top of BERT and the parameters except for BERT's last layer are fixed during training.

Pre-processing and Hyperparameters

All user mentions, URLs, hashtags and emojis are removed from the posts. We use the suggested settings from the original implementations [5, 29, 30] except for the following hyperparameters. For each hyperparameter tuning experiment, we randomly designated 20% of the data points in the training set as a development set. All possible combinations of candidate parameter values were tested and the optimal value was determined based on maximising the macro-F1 score on the development set.

For BERT, BERT-COVID, CANTM and CANTM-COVID, the batch size is searched from {16, 32, 64}. Since FD data contains posts with long textual length, we experiment with three truncation strategies [32]: keep the beginning (the first 300, 400, or 512 tokens), the end (the last 300, 400, or 512 tokens) or a combination of both strategies (the first 300 and the last 212 tokens). The optimal selection in each experiment is keeping the

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first 400 tokens and training with batch size as 32. The same truncated texts are used for BOW-LR and SCHOLAR. For SCHOLAR, we set embedding dimension as 500, chosen from {300, 400, 500, 600}.

Evaluation

- 1. Evaluation of overall performance: we compare CANTM and CANTM-COVID with baseline models based on 5-fold stratified cross validation on the augmented seven-class dataset. The average of macro-F1, accuracy and per-class F1 scores are reported.
- 2. Evaluation of data augmentation: we evaluate (1) whether the newly collected posts improve the performance on the minority classes; (2) whether the introduction of the AnimalVac class impacts the performance on the six human-related vaccine classes.

To compare the performance before and after re-balancing the human vaccine related minority classes, we construct two training sets (Training set(imbalanced) and Training set(balanced)) and a test set (Test set(six-class)). The data of the six topics except for MRE in the FD data is randomly split in the ratio of 7:3 in the case of Training set(imbalanced) and Test set(six-class). As for the MRE class, since it only consists of seven posts in the FD dataset, we include them in the Test set(six-class) only. The newly collected MRE posts are randomly split in the same ratio as above to complete the Training set(imbalanced) and Test set(six-class). The Training set(balanced) is the combination of Training set(imbalanced) and the rest of the new posts we collected during data augmentation.

To contrast the performance before and after the introduction of the new category AnimalVac, we randomly split the data points in the AnimalVac class into two parts (7:3) and add them into Training set(balanced) and Test set(six-class) respectively, that is, Training set(seven-class) and Test set(seven-class).

Table 4 presents the statistics of the training and test data for this set of experiments. We run each experiment five times and report the average of macro-F1 and accuracy scores.

Table 4. Labe	el count of the training	and test sets for	the evaluation of data
augmentation.	The target classes are i	n bold.	

Datasets	Cons	DPA	LF	MRE	PE	SEN	AnimalVac
Training set (imbalanced)	16	81	26	114	76	94	0
Training set (balanced)	97	81	82	114	76	94	0
Test set (six-class)	10	35	11	37	32	40	0
Training set (seven-class)	97	81	82	114	76	94	67
Test set (seven-class)	10	35	11	37	32	40	29

Results

Evaluation of overall performance: Table 5 presents the results of model comparison with 5-fold cross-validation. The pre-trained transformer-based models significantly outperform BOW-LR and SCHOLAR whose model structures are much simpler. CANTM shows increase in accuracy and macro-F1 scores compared with the strong

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baseline model BERT. Taking advantage of pre-training on an in-domain corpus of COVID tweets with a larger transformer model, BERT-COVID outperforms CANTM. CANTM-COVID further improves the performance, achieving the highest accuracy and macro-F1 scores. Models tend to perform better on the Cons, LF, MRE and AnimalVac classes. This is expected, since they consist of posts retrieved through class-associated keywords.

Table 5. Results of model performance on the augmented seven-class test dataset. The best results are in bold.

Model	Macro-	Aggurgay	F1 score						
Model	F1	Accuracy	Cons	DPA	LF	MRE	PE	SEN	AnimalVac
BOW-LR	0.67	0.67	0.62	0.62	0.72	0.77	0.52	0.50	0.83
SCHOLAR	0.65	0.66	0.65	0.56	0.67	0.88	0.46	0.43	0.89
BERT	0.74	0.75	0.79	0.63	0.65	0.92	0.54	0.59	0.95
BERT-COVID	0.80	0.80	0.90	0.73	0.83	0.94	0.64	0.63	0.97
CANTM	0.77	0.77	0.82	0.70	0.75	0.94	0.60	0.62	0.96
CANTM-COVID	0.84	0.84	0.91	0.77	0.86	0.96	0.67	0.72	0.97

Evaluation of data augmentation: we use CANTM-COVID for this set of experiments as it is the best performing model as shown above. The results are presented in Table 6. We also show the confusion matrices in Fig 2.

Table 6. Results of data augmentation evaluation of the CANTM-COVID model.

Training set	Test set	Macro-F1	Accuracy
imbalanced	six-class	0.57	0.69
balanced	six-class	0.67	0.72
seven-class	seven-class	0.69	0.75

Re-balancing the training set could increase accuracy by 3% and macro-F1 score by 10%. The recall scores of the two target minority classes (LF and Cons) grow from 0.31 to 0.49 and from 0.04 to 0.36 respectively, while the performance of the other four classes are not significantly influenced. As for the MRE class, 43% of posts in FD data can be correctly predicted if training with only the newly collected tweets for this class, either in imbalanced, balanced six-class or seven-class setting. We observe that the model could accurately identify all the short tweets in LF after data augmentation. However, it is still hard for the model to correctly classify long posts. Details about this shortcoming are discussed in the next section.

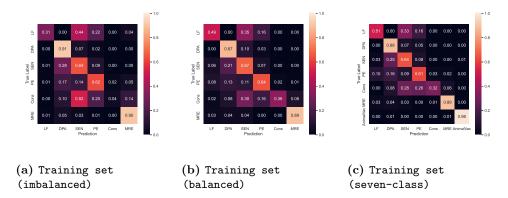
Introducing the AnimalVac class does not strongly impact the performance on the other six categories about human vaccination, which are the more important classes for this task. The model could accurately recognize 98% of posts regarding animal vaccination, denoting that animal vaccine posts are easily distinguishable.

As shown in Fig 2, PE and SEN posts are easily mis-classified as DPA (16% and 25% respectively. It is also hard for the model to distinguish LF from SEN and PE. The model struggles most on classifying the narratives about conspiracies. Only 32% of them can be correctly tagged even after data augmentation. We discuss the potential reasons and provide examples in the next section.

Furthermore, the drop in performance as compared to the results in Table 5 indicates that it is relatively easier for the model to learn and identify the augmented data collected through class-associated keyword matching, but hard to generalise to unseen domains, especially for the Cons class. It should be noted that we intentionally involve conspiracy stories that are not in the FD dataset (only "nano" and "deep state" appear in one post respectively after preprocessing). The LF class is less impacted since

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Fig 2. Confusion matrices for data augmentation evaluation



95% of new posts are collected through hashtags which are removed before training. However, our results still illustrate promising improvement in performance over the target topics, showing ability of model generalisation.

Discussion

Although our model performs well, we highlight the following challenges and limitations. We also provide some error analysis examples in Table 7:

Table 7. Misclassification examples

	True label	Prediction	Narrative
1	LF	SEN	This is XXX - three months old, five days after a round of vaccines, showing
			the distinct sign of stroke. She died two days laterthis type of asymmetry
			was common in the faces of the kids the day following vaccinationsKeep your
			eye, your focus on the MAIN GOAL: NO MANDATES period. No Mandates.
			No Mandates. Censorship is real.
2	LF	PE	Happy to be here after spending years suffering from Trump delusion syn-
			dromeIt seems the only policy Biden has spoken about is how he will mandate
			masks, which ultimately will lead to vaccine mandates. Biden is in the dark in
			terms of medical freedom. Trump for sure.
3	Cons	PE	We need to depopulate the planet. Also Bill Gates: Save your life with my
			vaccine.
4	SEN	DPA	Good News on Covid 19 vaccine: The result of the phase two trial of the Covid
			19 vaccine by Oxford University's Jenner Institute and Oxford vaccine group is
			very positive. The result showed a strong immune response in both parts of
			the immune system. The vaccine provoked a T cell response within 14 days of
			vaccination that can attack cells infected with the Covid 19. Participants who
			received the vaccine also had detectable neutralising antibodies important for
			protection against Covid 19. Oh God, please make this vaccine work so that we
			can go back to our normal world. Amen/Ameen.

1. Long narratives involving multiple topics are easily misclassified. As shown in Table 7, the first post cites safety considerations and side effects of vaccination as grounds for objecting mandatory vaccination. In this case, the classifier incorrectly assigns the SEN label. The fourth claim shows another example whose true label is SEN while the model falsely tags it as DPA. The classifier is confused

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- because the post first elaborates on the development of the COVID-19 vaccine to support the opinion towards the necessity of the vaccine in the last sentence.
- 2. Dataset and model need to be updated over time, especially for the DPA and Cons classes, since new conspiracy theories are emerging continuously. The poor performance on the Cons class (see Fig 2) illustrates that the model is finding it hard to generalise to new narratives. Also, progress concerning development, testing and provision of COVID-19 vaccination is fast changing. The samples in the DPA class were collected by First Draft in 2020 and most of the posts in their dataset refer to the announcement of registration of the world's first COVID-19 vaccine by Russia, thus lacking examples of more recent events. Consequently we observe that the model tends to infer an unexpected correlation between Russian and the DPA class.
- 3. The size of our current dataset is still relatively small and this may result in model bias. As shown in the second example in Table 7, the mention of "Biden" and "Trump" may be the reason for the misclassification as they frequently appear in posts pertaining to politics. The class-associated words generated by CANTM-COVID confirm our assumption: "trump" is highly associated with the PE class. Similarly, Bill Gates, who is often linked to conspiracy theories, is frequently involved in narratives about economics in the training set. In fact, "gates" is among the top 5 topics for the PE class, which may explain the misclassification of the 3rd conspiracy post. The class-associated keyword-based data augmentation may also make the model overly dependent on these target terms as discussed above.

Conclusion

This paper proposed a novel seven-way classification task for categorising online vaccine narratives. We augmented an existing six-class dataset semi-automatically, leading to a more balanced data distribution and the inclusion of an additional seventh category of posts related to animal vaccines. We experimented with strong baseline models and our best model CANTM-COVID achieves an accuracy score of 0.84 using 5-fold cross-validation. We also show that data augmentation of minority classes helps to produce better models, without significantly impacting the performance on the remaining classes. Moreover, the addition of the new animal vaccine category does not influence significantly model performance on the original six human vaccine related classes.

In our discussion, we highlighted the main challenges of this task and the current limitations of our model. Future work will focus on addressing some of those challenges, including development of models capable of dealing with longer posts.

Last but not least, our vaccine narratives classifier is made available through an API for reproducibility reasons. We believe this is a significant contribution towards understanding and tracking online debates around vaccine safety and hesitancy.

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