Insta-VAX: A Multimodal Benchmark for Anti-Vaccine and Misinformation Posts Detection on Social Media

Mingyang Zhou\textsuperscript{1}, Mahasweta Chakraborti\textsuperscript{1}, Sijia Qian\textsuperscript{1}, Zhou Yu\textsuperscript{2}, Jingwen Zhang\textsuperscript{1}
\textsuperscript{1}University of California, Davis
\textsuperscript{2}Columbia University
{minzhou, mchakraborti, sjqian, jwzhang}@ucdavis.edu
{zy2461}@columbia.edu

Abstract
Sharing of anti-vaccine posts on social media, including misinformation posts, has been shown to create confusion and reduce the public’s confidence in vaccines, leading to vaccine hesitancy and resistance. Recent years have witnessed the fast rise of such anti-vaccine posts in a variety of linguistic and visual forms in online networks, posing a great challenge for effective content moderation and tracking. Extending previous work on leveraging textual information to understand vaccine information, this paper presents Insta-VAX, a new multi-modal dataset consisting of a sample of 64,957 Instagram posts related to human vaccines. We applied a crowdsourced annotation procedure verified by two trained expert judges to this dataset. We then bench-marked several state-of-the-art NLP and computer vision classifiers to detect whether the posts show anti-vaccine attitude and whether they contain misinformation. Extensive experiments and analyses demonstrate the multimodal models can classify the posts more accurately than the uni-modal models, but still need improvement especially on visual context understanding and external knowledge cooperation. The dataset and classifiers contribute to monitoring and tracking of vaccine discussions for social scientific and public health efforts in combating the problem of vaccine misinformation.

Introduction
Changes in the media landscape, especially with the rise of social media, have accelerated the creation and spread of disinformation and misinformation on a global level\cite{vosoughi2018spread, roy2018spread, johnson2020building}. Exposure to anti-vaccine sentiments or associated vaccine misinformation can form false beliefs, arouse negative emotions, and reduce pro-vaccine attitudes, leading to vaccine hesitancy\cite{betsch2011disinformation, featherstone2020vaccine}. On one hand, anti-vaccine information can simply signal an opinion that is against vaccines. On the other hand, vaccine misinformation is defined more clearly as “a broad category of claims that inadvertently draws conclusions based on wrong or incomplete information”\cite{southwell2019defining} in the context of discussing vaccines. Vaccine misinformation thus specifically refers to false or inaccurate information judged by the scientific community’s consensus contemporary with the time period\cite{tan2015science}. For instance, a personal anti-vaccine narrative that shows negative emotions toward vaccines does not necessarily contain misinformation. On the contrary, vaccine misinformation contains explicit or implicit claims or arguments based on false or incomplete information that argue about the scientific research, development and production, safety, or effectiveness of vaccines (e.g., the claim that vaccines cause Autism in children or the claim that vaccines are developed for population control). Although past research has shown many anti-vaccine messages circulated online contains misinformation claims\cite{dum2017identifying}, it is crucial to conceptually and operationally differentiate these two categories. If social media is ought to fact-check and tag misinformation, any automated approaches need to clearly set the boundaries that distinguish opinions from misinformation claims. While facing the challenges of vaccine hesitancy and recurring pandemic threats, accurately and efficiently identifying vaccine misinformation on social media while preserving personal free opinion expressions is a core issue to be tackled by the computational social science community. So far, past literature in NLP has not distinguished the two categories well and some have oversimplified anti-vaccine opinions as medical misinformation\cite{wang2020natural}.

The absence of tracking and moderating vaccine misinformation has left individuals vulnerable to strong persuasive agendas. Given limited attention and a lack of expertise, a layperson may be influenced by the wrong information without the capacity to assess the credibility and accuracy of its claims. Accordingly, recent efforts have focused on empowering individuals through developing algorithms that fact-check online information and provide related resources\cite{zhang2021overview}. A number of recent research has used multiple content analytical approaches to quantify anti-vaccine stance on social media. For example, Broniatowski et al.\cite{broniatowski2020anti} categorized 204 Facebook pages and tracked the changes in framing of vaccination opposition over 10 years. Guidry et al.\cite{guidry2020anti} analyzed 1000 Pinterest posts about HPV vaccination and found visual cues (e.g., a large needle) associated with anti-vaccine contents.
Although many studies have extracted thematic topics in anti-vaccine information, few made efforts to distinguish anti-vaccine posts and misinformation posts. In addition, the majority of previous work focused on textual information. As contents on social media are increasingly relying on visuals to frame or supplement arguments and opinions, understanding the visual features associated with anti-vaccine information and misinformation is of great importance to enrich our classification of anti-vaccination communications on social media (Seltzer et al. 2017; Wang, Yin, and Argyris 2020).

To address the gaps, this paper presents a curated large-scale dataset of 64,957 Instagram posts relevant to vaccine discussions. We benchmark several state-of-the-art (SOTA) machine learning models by using different modalities to classify vaccine posts on dimensions of vaccine attitude (i.e., anti-vaccine or none) and vaccine misinformation (i.e., misinformation or none) based on an annotated sample of 5000 posts. The rationale for focusing on binary classifiers is that when considering the downstream impacts of the social media information, it is anti-vaccine and misinformation posts that have significant negative impacts on public health (Southwell et al. 2019). Experiments show that multimodality is helpful to improve the detection accuracy, but the help from visual cues is only incremental due to the challenges of visual context understanding. We hope our findings point to more effective directions for multi-modal machine learning methods to address vaccine misinformation content moderation. We provide insights into the different visual and textual cues that are highly correlated with anti-vaccine attitude and misinformation to help the general audience to identify such social media content.

### Related Work

#### Anti-Vaccine and Vaccine Misinformation Posts

Anti-vaccine discourses and vaccine misinformation encompass multiple and complex dimensions of reasoning and emotions, with explicit arguments or implicit suggestions involving references to nuanced social contexts. Prominent explicit arguments include vaccines and their ingredients cause illnesses and adverse effects (Guidry et al. 2015). These beliefs are supported by a generic frame that argues the scientific community cannot be trusted because of inherent uncertainties or potential malpractices (Zimmerman et al. 2005). In addition, personal narratives eliciting strong emotional resonances with the viewers are also typical types of messages featured in such anti-vaccine discourses where stories featuring children injured from vaccines are common examples (Margolis et al. 2019). The second prominent type focused on the public’s declining trust in authorities and prompts conspiracy ideation regarding the vaccination programs, speculating on how governments and pharmaceutical companies cover up the “truth of vaccines” from the public (Davies, Chapman, and Leask 2002). Lastly, the discussions on vaccines can also invoke religious or policy oppositions centering on the ethical grounds of vaccine mandates. Although this type of discussions does not directly touch upon calculations of vaccine benefits and risks about specific diseases, it can arouse strong political and emotional reactions that can negatively impact favorable opinions toward vaccines (Haber, Malow, and Zimet 2007).

According to the definition of vaccine misinformation (i.e., false or inaccurate information judged by scientific consensus) and based on previous literature operationalizing vaccine misinformation (Burki 2019; Southwell et al. 2019), we deem explicit claims and arguments for lack of vaccine necessity, ineffectiveness, lack of safety, danger, unknown harms of vaccines, and vaccine conspiracies as misinformation because they are false claims inconsistent with established expert consensus and cumulative scientific evidences. Vaccine conspiracies are deemed as misinformation because they draw conclusions based on pure speculations or false and incomplete information. Other than these, we deem personal stories or expressive opinions that do not involve claims as non-misinformation but as indicating attitudes toward vaccines. Figure 1 provides two example posts, with (a) labeled as both anti-vaccine and containing misinformation (i.e., claiming vaccines cause autism) whereas (b) labeled as anti-vaccine without presence of misinformation (i.e., just showing anti-vax bracelets).

![Figure 1: Sample anti-vaccine Instagram posts that are labeled to having misinformation versus not having misinformation.](image)

### Misinformation Detection

Previous research on misinformation detection has utilized a variety of approaches, including analyzing content features (Ito et al. 2015; Hu et al. 2014), social context features (Shu et al. 2017; Volkova and Jang 2018; Iacchini et al. 2017), and leveraging knowledge graphs (Ciampaglia et al. 2015) and the wisdom of the crowds (Qazvinian et al. 2011). Recently, deep learning-based methods that abstract a high-level representation of data has been often adopted to conduct misinformation detection (Li, Cai, and Chen 2018; Yu et al. 2019; Dong et al. 2019).

However, given the complexity of anti-vaccine and misinformation contents, effective machine-learning models that can understand and extract useful textual and visual signals from social media posts on vaccine attitude and misinform-
The innovation of our paper is twofold. First, our annotations and classifiers distinguished misinformation from anti-vaccine attitude in Instagram posts. Second, we present experiments with several SOTA machine learning models and point out the challenges of employing different modalities. With our findings, we hope to spur future research to build strong anti-vaccine and misinformation classifiers by better leveraging the multimodal context.

**Insta-VAX Dataset**

**Data Collection**

To collect Instagram posts that express diverse opinions toward vaccines, we carefully curated 39 Instagram hashtags that are related to vaccines, shown in Appendix. From the 39 hashtags, we collected 494,249 posts. To further clean the dataset, we deleted the posts about animal vaccines via keyword matching. We used a large corpus of keywords that covered pet food brands, stores, rescue organizations, vet diseases, and breeds, etc. Posts with multiple mentions of the keywords from the list were excluded. We also filtered out posts whose captions contained non-English texts detected by Google Translate API. As a result, we obtained a total sample of 64,957 posts published between June 2011 and April 2019.

**Ethics**

In line with Instagram data policies (Instagram) as well as user privacy, we only gathered publicly available data with target hashtags that is obtainable from Instagram.

**Crowdsourced and Expert Annotations**

We combined crowdsourcing and expert annotation approaches to label the posts. At the first stage, we used Amazon Mechanical Turk (MTurk) for crowdsourcing. We selected a random sample of 4,997 posts, and split them further into 100 batches of 50 posts, allowing four independent workers to work on each batch. Workers were asked to label the post’s attitude toward vaccine and whether the post has misinformation claims about vaccines in each post based on both images and captions. Workers were provided with scholarly definitions of anti-vaccine attitudes and vaccine misinformation claims. Specifically, we asked two questions: 1 “What is the attitude of the post?” (response choices included ‘anti-vaccine,’ ‘pro-vaccine,’ and ‘neutral’) and 2 “Does the displayed post contain misinformation?” (‘yes,’ ‘no,’ and ‘not sure’). Responses were recorded as binary inputs as anti-vaccine vs. none and misinformation vs. none. Among the 5,000 posts, three did not retain original images and thus were eliminated from further analyses, resulting in 4,997 posts for annotation. Each worker was paid 2 dollars for annotating 50 posts.

After receiving the crowdsourced labels, we trained two expert coders, one undergraduate and one graduate student, to examine and finalize the coding of vaccine attitude and misinformation claims for all the posts. The two coders were trained by a senior researcher specializing in public health and vaccine misinformation communication. Specifically, the two coders examined scientific and organizational webpages (i.e., CDC, FDA, HHS) on common vaccine misinformation claims.

Each coder independently examined a randomly selected sample of 100 posts and established high inter-coder reliability (anti-vaccine attitudes: Cohen’s Kappa = 0.82; misinformation: Cohen’s Kappa = 0.78). The two coders discussed and resolved all disagreements. Then the two coders proceeded to check the labeled posts from MTurk, with each independently checking half of the sample. We examined the crowdsourced results by the criteria of majority votes, which is defined as receiving the same vote from three out of four workers on the post. For question 1 regarding vaccine attitude, 84.9% posts received clear majority votes whereas question 2 regarding misinformation received 75.8% majority votes.

For the posts receiving majority votes, the two coders checked and verified if they were correct. For the posts that received split votes, the coders provided final judgements. Thus, we determined the ground truth basing on both crowdsourced votes and expert judgements, and we used the finalized labels to train the models.

| Total posts | 64,957 |
| Labeled posts | 4,997 |
| Anti-vaccine posts | 1,373 |
| Misinformation posts | 1,115 |
| Misinformation & Anti-vaccine Posts | 1,101 |
| Training set | 4,000 |
| Testing set | 997 |
| Avg. words per post | 55.27 |
| Avg. words per post (labeled) | 51 |

**Table 1: Insta-VAX dataset statistics**

**Dataset Details**

In table[1] we provide an overview of the statistics of our dataset. There is a clear overlap between the posts that contain misinformation and that express anti-vaccine attitudes, with 98.7% misinformation posts containing anti-vaccine at-
titudes. However, only 80.2% posts that express anti-vaccine attitudes contain misinformation. This shows the possibility of differentiating the two content categories challenges the simple assumption with previous research (Wang, Yin, and Argyris [2020]) which collapse the two. The annotated sample was then split into 80% for training, and 20% for testing using stratified split.

Experiment Setting We set up baseline machine learning models, which leverage different inputs from our datasets to detect anti-vaccine posts and misinformation posts. By analyzing the limitations of the baseline models, we hope to provide insightful suggestions for future work on multi-modal misinformation detection using datasets similar to Instagram posts.

Models
We experimented with three SOTA uni-modal models and multi-modal models to detect anti-vaccine and misinformation posts. Specifically, the uni-modal models either use the images or the texts to classify a post, while the multi-modal models use both texts and images as the inputs. All the output layers for classification are multi-layer perceptrons followed by a softmax layer.

Text-Only Uni-modal Models First, we mainly consider the state-of-the-art transformer-based pre-trained language model BERT (Devlin et al. [2019]). Given the post text, we tokenize the input text into WordPieces (Wu et al. [2016]) and feed it into BERT. BERT then converts the text tokens into embedding vectors and processes the vectors through a multi-layer transformer architecture (Vaswani et al. [2017]) to learn contextualized embeddings of the input text. Finally, we extract the representation of [CLS] token as the global representation of the input text and feed it into the output layer to classify the text.

Image-Only Uni-modal Models For Image-based Uni-modal Models, we employ the convolutional neural networks, ResNet-152 (He et al. [2016]). Given an input image, we process the image through ResNet-152 and extract the average pooling as output, which yields a 2048-dimensional vector for each image. The extracted vector is then forwarded through the output layer to perform classification.

Multi-Modal Models For multi-modal models, we experiment with the state-of-the-art method UNITER (Chen et al. [2020]). UNITER is an extension of the BERT model that takes the concatenation of image and text and fuses the two modalities through a single stream multi-layer transformer to extract the joint representation. The joint representation is then forwarded through the output layer to classify the multi-modal context into different labels. UNITER encodes the input image as a set of visual features for the detected region of interests (ROI) from a pre-trained object detector (Anderson et al. [2018]).

Experiments
Given the image and the caption of an Instagram post, we evaluate the three proposed methods on two binary classification tasks: (1) what is the attitude of the Instagram post toward vaccine (2) whether the Instagram post contains misinformation. By comparing the performance of the three proposed methods that leverage input from different modalities, we can understand how each modality is contributing to help the model to detect the anti-vaccine sentiment and the misinformation content. As our dataset is highly imbalanced, we use macro-F1 instead of accuracy as the evaluation metric. During the fine-tuning stage our data, we also experiment with two variances. First, as the images of the Instagram are often memes, we also extract the embedded text (OCR) from the images with Google Vision API as an additional resource to study the contribution from vision. Next, for the transformer-based methods like UNITER and BERT, we experiment both settings including and excluding of performing weakly-supervised learning with their proposed pre-training objectives on our un-annotated raw data.

Training Details
We initialize Transformer-based models such as BERT and UNITER with pre-trained BERT-based, uncased model weights. For image-only uni-modal model, we initialize Resnet-152 with the pre-trained weights obtained from the ImageNet Classification task (Deng et al. [2009]). All parameters of the transformer-based models are optimizable. However, for image-only uni-modal model, we only fine-tune the last ResNet block and the final fully connected layer to maintain the consistency of the early level features. For all models, we use Adam optimizer (Kingma and Ba [2015]) with a linear warm-up for the first 5% of training and set the learning rate to 5e − 5. The learning rate is decayed linearly proportional to the training steps. Since the dataset labels are not balanced, we weigh the class labels by their inverse frequency during optimization. Fine-tuning is conducted on 2 Nvidia RTX-2080 Ti GPUs for 5 epochs. When pre-train BERT and UNITER on the raw Instagram posts, train the model for 10 epochs on 2 Nvidia RTX-2080 Ti GPUs. For the weakly supervised learning, we also use Adam Optimizer with the learning rate set to 5e − 5 to optimize the model.

Results and Analysis
Quantitative Results
Table \ref{tab:table_name} summarizes the model performances on our test set for the task of detecting posts that express anti-vaccine attitudes and posts that contain misinformation. Both image-only baseline and text-only baseline have significantly outperformed the majority vote baseline, demonstrating that both modalities are useful for models to learn the appropriate knowledge to perform the task. However, the text resource is clearly more helpful than the visual context for both classification tasks, given that the BERT model achieves over 12% classification accuracy against the image-only baseline. Despite that, UNITER, which takes input from both modalities,
Table 2: Results on detection posts containing anti-vaccine sentiment or misinformation from methods with different combination of input modalities.

| Modalities | Models | Text Src | Raw Finetune | anti-vaccine | misinformation |
|------------|--------|----------|--------------|--------------|---------------|
|            | Majority Vote | -        | -            | 42.3%        | 43.8%         |
| Image      | ResNet-152   | -        | -            | 66.9%        | 69.3%         |
| Text       | BERT        | caption  | -            | 84.5%        | 79.9%         |
|            |            | caption + OCR | -            | 84.6%        | 81.3%         |
|            |            | caption   | MLM          | 85.5%        | 82.5%         |
|            |            | caption + OCR | MLM          | 87.9%        | 85.1%         |
| Image+Text | UNITER      | caption  | -            | 85.6%        | 82.0%         |
|            |            | caption + OCR | -            | 86.2%        | 82.5%         |
|            |            | caption   | MLM          | 87.7%        | 85.0%         |
|            |            | caption + OCR | MLM          | 89.1%        | 87.3%         |

Figure 2: Plot of the attention map on image and the caption on the Instagram posts on samples of the anti-vaccine Instagram post and misinformation post where the model predict correctly.

achieves the best performance. The help from vision context is still quite limited as the improvement over BERT is relatively incremental. One possible reason is that many images on Instagram posts are memes containing dense OCR texts but not many meaningful visual objects. By extracting the OCR texts from the image, and encoding it as part of the text input, we can observe clear improvement on both BERT and UNITER. We also observe that the transformer-based models significantly benefit from the weakly supervised fine-tuning on the raw Instagram posts. When fine-tuning BERT and UNITER with masked language modeling, they both gain over 2% improvement on anti-vaccine detection and over 3% on misinformation detection. We hypothesize that such pre-training objectives can alleviate the severe domain shift between the original pre-training corpus used by BERT and our vaccine centered Instagram data.

Attention Visualization

To understand how the model interprets the multi-modal context when it makes the prediction result, we visualize the attention predicted by the model on the image and text input when our model successfully detects the posts. Some samples are presented in Figure 2. The model can attend to the salient text information that has strong indication to either anti-vaccine sentiment or misinformation, such as the hashtags ‘#vaccineskill’, ‘#vaccineinjury’, and ‘#rethink vaccines’. In comparison to the accurate attention to the texts, the model struggles to attend to critical objects that may be correlated to anti-vaccine sentiment. In both examples, the model attends more to the baby face instead of attending to the needles eliciting negative thoughts or emotions like fear. Especially on the misinformation example, the model concentrates on the salient local parts of the baby’s face. We hypothesize the failure to attend to the more relevant image regions comes from the bias in the visual representation of UNITER, which is more prone to common objects observed in their original training datasets. Future work needs to build image encoder mechanisms that have less reliance on the supervision from a pre-training corpus, such as the grid-based image feature extractor employed by MMBT (Kiela et al. 2019).

Ablation Study on Hashtags

Hashtags are important segments in Instagram captions, which often contain keywords that indicate the attitude towards vaccines. To avoid the model achieving high accu-
Error Analysis

To further understand the complexity of social media vaccine posts, we examine samples from the test set that our best model UNITER predicts incorrectly. Such examples are shown in Figure 3. Overall, our best model can detect the post that contains anti-vaccine attitudes more accurately, in comparison to detecting posts that contain misinformation, with prediction accuracy of 79% and 73% respectively.

The majority of anti-vaccine posts that are predicted correctly by our model contain key phrases or hashtags that express strong negative sentiments toward vaccines, such as ‘#antivax’, and ‘#vaccinetoxic’. Our model experiences a hard time classifying posts with ambiguous, suggestive, or sarcastic expressions. Examples are shown in Figure 3 where the images contain vaccine-irrelevant objects and the captions use suggestive arguments. The full meaning is only interpretive when combing texts and images together. Errors on these posts suggest future multi-modal models need to build better mechanisms to extract visual representation and ground such visual information into its associated textual context.

As posts containing misinformation are highly correlated with posts that express anti-vaccine attitudes, a large portion of the failure detection cases are also shared. Example cases shown in Figure 3 do not contain clear false claims in captions or hashtags and the images are also seemingly irrelevant. Correct identification on the misinformation about vaccines and autism requires external knowledge. As shown in Table 2, performing weakly supervised learning on the corpus related to this topic would dramatically help the model to obtain such knowledge to detect misinformation, which helps the multi-modal model to gain over 5% detection accuracy. However, to accurately detect the misinformation, background fact-checking and learning with domain specific knowledge needs to be incorporated.

Textual and Visual Characteristics

Given the above-mentioned limitations, we conduct further analyses to identify textual and visual characteristics that are prominent in anti-vaccine posts and misinformation posts. These insights could be used to build more accurate models to move forward research on social media vaccine content moderation.

Textual Cues and Trends

To identify textual characteristics for anti-vaccine and misinformation posts, we compute the relative importance of the words from the Instagram captions and the embedded texts that are correlated with the anti-vaccine and the misinformation posts. We design a score function to compute the word
Most Correlated Objects
Suit, Syringe, Drink, Food, Container
Food, Tie, Drink, Syringe, Container

In order to understand the visual characteristics across the two dimensions of anti-vaccine attitudes and misinformation, we analyze the correlation between the objects appeared in the images and the posts. We apply Google Vision API to detect the objects on each image, and in total we have 256 distinct object types detected in our dataset. Similar to finding the important words for each class, we also employ the importance score defined in the previous section to identify the salient objects that are highly correlated with anti-vaccine and misinformation. The top 5 objects with the highest importance scores for anti-vaccine posts and the misinformation posts are summarized in Table 3.

There is a big overlap between the salient objects that appear in the posts with anti-vaccine sentiment and the posts containing misinformation. The frequent appearances of “food”, “drink”, and “container” in anti-vaccine posts are in general consistent with some of their claims that lifestyles and holistic food habits can partially or wholly replace vaccination. The frequent reference to syringes in the anti-vaccine images is consistent with previous research suggesting anti-vaccine and misinformation posts often exploit the negative emotions such as fear (Featherstone and Zhang 2020), anger, and pain associated with needles to promote vaccine hesitancy.

Table 3: The top-5 image objects that is highly correlated with the Instagram posts with anti-vaccine sentiment or misinformation.

| Task          | Most Correlated Objects          |
|---------------|----------------------------------|
| Anti-Vaccine  | Food, Tie, Drink, Syringe, Container |
| Misinformation | Suit, Syringe, Drink, Food, Container |

Visual Cues and Trends
In order to understand the visual characteristics across the two dimensions of anti-vaccine attitudes and misinformation, we analyze the correlation between the objects appeared in the images and the posts. We apply Google Vision, we analyze the correlation between the objects ap-
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### Instagram Hashtags

#antivaccine, #provaccine, #vaccineinjuryawareness, #antivaccines, #provax, #vaccines, #antivax, #provaxx, #vaccines_facapts, #antivaxmemes, #provaxxer, #vaccinesharm, #antivaxxer, #saynotovaccines, #vaccineskill, #dontvaccinate, #vaccinate, #vaccineskillkids, #dontvaxx, #vaccinated, #vaccinesavebro, #educatebeforeyouvaccinate, #vaccinateyourkids, #vaccinesavellives, #measles, #vaccination, #vaccineswork, #measlesoutbreak, #vaccinations, #vaccinesworks, #novaccines, #vaccine, #vaccinethread, #provacc, #vaccinefree, #vax, #provaccination, #vaccineinjury, #vaxxed

### Keywords for Animal Vaccine Posts Filtering

| Keywords Type | Keywords |
|---------------|---------|
| Pet Health    | adenovirus, parainfluenza, spay, neuter, parvovirus, petcare, deworm, petcare, breed, spay, neuter, kennel, rabies, rabid, fvr, distemper, veterinarian, vet |
| Pet Brands    | dogwalker, iams, orijen, avoderm, dogswell, merrick, spca, petco, aspca, petsmart, shelter, rescue |
| Pet Breeds    | sphynx, retriever, labrador, bulldog, beagle, poodle, rottweilers, terrier, doberman, chiuhaua, pinscher, dachshund, pedigree, pug, husky, pomeranian, corgi, mastiff, shiba, maltese, bichon, hound, dalmatian, spaniel, birman, ragdoll, siamese, shitzu, akita |
| Animals       | animal, dog, pet, cat, pup, puppy, canine, feline, cow, cattle, livestock, horse, poultry, equine |

Table 4: The collected keywords for animal-related vaccine Instagram post filtering

### Additional Visual Cue Analysis

We have also conducted additional visual cue analysis by examining the usage of the color spectrum. We employ HSV (Hue, Saturation, Value/Brightness) color scheme, where we compute histograms for the pixel distribution over the three channels from our dataset. Then, we compute average HSV histograms for the group of posts for each class. We compare the average HSV histogram between anti-vaccine posts and non-anti-vaccine posts. Similarly, we also conduct the comparison between the average HSV histogram of misinformation posts and the ones that does not contain misinformation. The results are summarized in Figure 5 and Figure 6.

### Dataset Annotation Interface

We demonstrate our data annotation interface in Figure 7. On the left-hand side, we detailed the instruction to help annotators to accomplish the task. The image and the associated captions as well as text presented in the image are displayed in the middle and on the right-hand side. Finally, at
Figure 7: Interface to collect the annotation on anti-vaccine and misinformation post from the Amazon Mechanical Turk.

**Instructions**

This task asks you to judge the attitude towards vaccines as indicated from the shown social media post:

1. Please review all components of the post including captions, images and texts, and select an option.
2. If you think the post contains misinformation, please select an option too.
3. When you annotate a post, you need to look only into the information presented in the post. You do not need to follow links to external websites or resources.
4. Respond to both questions to proceed. After answering the questions, please hit the ‘Submit’ button.
5. If you see the post is irrelevant to human vaccines, please hit the ‘Irrelevant’ button.
6. Your entries are automatically saved upon every ‘submit’ and annotation resumes when you log back in using your username. Results are not lost if you close browser.

**What is the attitude of the post?**
- Anti-vaccine
- Pro-vaccine
- Neutral

**Does the displayed post contain misinformation?**
- Yes
- No
- Not Sure

**Caption:**

Have you had your flu shot yet? Children, adolescents, pregnant women, elderly people and those with chronic health conditions are at the greatest risk of developing flu complications. FluVaccines FluVaccine Flufree FluFlu WinterFlu Flufighting FluFluVaccines

**Rendered Image text:**

PHARMASAVE: It’s not too late for a flu shot. Speak with your Pharmasave pharmacist, Canada’s community pharmacy.

**Ethical Statement**

Our dataset and code will be publicly available upon notification of the paper acceptance. We will publish the data in agreement with Instagram’s Terms and Conditions (Instagram), where we would not directly share the original post content but just distribute the Post ID’s. Researchers can then simply retrieve post content through these IDs by using open-source APIs such as Instaloader.