Detecting Medical Misinformation on Social Media Using Multimodal Deep Learning

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Abstract—In 2019, outbreaks of vaccine-preventable diseases reached the highest number in the US since 1992. Medical misinformation, such as antivaccine content propagating through social media, is associated with increases in vaccine delay and refusal. Our overall goal is to develop an automatic detector for antivaccine messages to counteract the negative impact that antivaccine messages have on the public health. Very few extant detection systems have considered multimodality of social media posts (images, texts, and hashtags), and instead focus on textual components, despite the rapid growth of photo-sharing applications (e.g., Instagram). As a result, existing systems are not sufficient for detecting antivaccine messages with heavy visual components (e.g., images) posted on these newer platforms. To solve this problem, we propose a deep learning network that leverages both visual and textual information. A new semantic-and task-level attention mechanism was created to help our model focus on the essential contents of a post that signal antivaccine messages. The proposed model, which consists of three branches, can generate comprehensive fused features for predictions. Moreover, an ensemble method is proposed to further improve the final prediction accuracy. To evaluate the proposed model’s performance, a real-world social media dataset that consists of more than 30,000 samples was collected from Instagram between January 2016 and October 2019. Our 30 experiment results demonstrate that the final network achieves above 97% testing accuracy and outperforms other relevant models, demonstrating that it can detect a large amount of antivaccine messages posted daily. The implementation code is available at https://github.com/wzhings/antivirus_detection.

Index Terms—Antivirus detection, attention mechanism, multimodal feature fusion, ensemble method

I. INTRODUCTION

CHILDHOOD vaccine hesitancy is a complex public health problem in the United States (US) [1]. The increasing number of under-vaccinated children is linked to parental delay or refusal of vaccines. These vaccine-hesitant parents often seek health information (including vaccines) on social media. Social media applications have thus contributed at least in part to the rapid growth of the antivaccine movement [2]. Recently, image-sharing social media platforms (such as Instagram, Snapchat, and Pinterest) are growing in popularity. Users of these platforms include young mothers from low-income and underserved populations who are more likely to trust social media for health information [3]. To counteract the large-scale spread of antivaccine messages to these vulnerable populations, it is urgent to develop an automatic and intelligent antivaccine detection system.

We chose Instagram as our target image-sharing social media platform because Instagram is leading among all other image-sharing platforms with 500 million daily active users [4]. The majority of Instagram users consist of young women from diverse backgrounds [3], thus suitable for our purpose of counteracting the propagation of antivaccine posts via social media.

Instagram, like other image-sharing platforms, allows users to include multimodal content in their posts, including images, captions, and hashtags, as illustrated in Fig. 1. These multimodal elements in an Instagram post largely encompass (1) visual elements (e.g., photographs and posters), and (2) textual elements (captions, words in images, and hashtags). All of these are important for detecting antivaccine themes in a social media post. First, images draw more engagement from the audiences (e.g., likes and comments) than texts alone [5]. Captions in posts are unarguably an important means through which the users deliver the main theme of their posts. However, given the increasing surveillance for misinformation on social media, savvy users opt for overlaying texts on an image to subvert the regulation [6], [7]. Lastly, many social media users employ hashtags like catchphrases wherein they succinctly summarize their main claims in their attempt to make their posts identifiable by like-minded crowds [8]. Given the importance and relevance of visual and textual elements in antivaccine messages, it is necessary to leverage all the multimodal information in social media posts. The neglect of an element could result in failures in detecting antivaccine messages, as indicated in Fig. 1(a) through Fig. 1(c).

Nonetheless, most prior studies only involve a small subset of textual components (i.e., posters’ comments) when investigating antivaccine messages [9]–[11]. The lack of comprehensive multimodality consideration in these prior studies therefore limits their abilities to accurately capture the antivaccine theme in social media posts, which are increasingly visual and textual.

The primary goal of this study, therefore, is to develop a reliable multimodal network to detect antivaccine messages on social media. Considering multimodality to achieve highly accurate predictions is essential for detecting antivaccine messages because both false positives and false negatives can have detrimental effects. Specifically, frequent false positives will lead to backlash from social media users who feel that their posts are unfairly demoted and censored; false negatives will

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fail to suppress the propagation of antivaccine messages.

The proposed model architecture entails multiple branches to extract features of images, words in images, captions, and hashtags in social media posts. The multimodal features are fused using attention mechanisms to produce comprehensive representations for the final detection. For the antivaccine detection task, the attention mechanism is implemented as a neural network model layer that helps the model to assign more weights to the essential content of antivaccine messages and improves the proposed model performance. None of the prior studies have considered all of these in one study. To develop and validate our model, we collected more than 30,000 Instagram posts. The resultant detection accuracy rate of our proposed model is the highest reported in the literature.

To summarize, our main contributions are as follows: (1) an end-to-end multimodal feature fusion network; (2) two types of attention mechanisms applied to visual and textual contents; and (3) two modules for projecting and fusing multimodal features. These contributions fill an important gap in the prior studies by considering multimodal information in antivaccine social media posts and help improve the algorithmic detection of medical information.

II. RELATED WORK

We review recent works about misinformation detection on social media, such as fake news, hate speech, health misinformation, and finally antivaccine messages. In the literature review, we focus on the strengths and weaknesses of each approach.

A. Fake News Detection

The innovative fake news detection models have leveraged both visual and textual information, but still are limited in the following aspects. For example,

- A recurrent neural network (RNN) was proposed to fuse images, text, and social contexts with attention mechanisms in order to detect fake news [12]. A limitation of this approach is that text information and social contexts in the post were represented by the same method. Moreover, the attention mechanism was only applied to visual components, not to the textual counterparts.
- To enable proposed models to have greater generalizability, a deep learning network with memory blocks was proposed to save event-invariant information [13]. For an input message, the model can output features shared among the same events and make decisions on the shared features. However, this method did not have an effective way to process hashtags in the message.
- A generative adversarial network was proposed to generate event-invariant multimodal features to detect fake news [14]. A text-based convolutional neural network (text-CNN) was proposed to extract textual features in the message. However, textual context information was not considered in this approach.
- A multimodal, variational auto-encoder coupled with a binary classifier was proposed to detect fake news [15]. An encoder and a decoder were developed to learn a shared multimodal representation of each message. Nevertheless, hashtag information was not employed during the model training.

B. Hate Speech Detection

Hate speech refers to objectionable speech that encourages violence or expresses hate towards people [16]. Some prior studies have employed deep learning models that leveraged multimodal information to detect hate speech but with room for improvements, like in fake news detection systems. Some researchers proposed to fuse multimodal information by the simple concatenation. For example,

- To detect misogynistic contents on social media, in [17], a pre-trained AlexNet model [18] was proposed to extract visual features from images, and a pre-trained word2vec embedding model [19] was selected to represent textual features in the posts. The two types of extracted features were then concatenated directly to be processed to predict whether the input post contained misogynistic information or not. The pre-trained models were not considered to be fine-tuned during the model training.
- A deep learning model that leveraged both visual and textual information to detect hate speech on Internet memes [20]. A pre-trained VGG16 model [21] was employed to extract visual features from images. The text in images was first extracted by an Optical Character Recognition (OCR) algorithm. The OCR results were then processed by a pre-trained BERT system [22]. After that, the extract visual and textual features were concatenated directly to be classified whether the input is a hate speech post or not. The pre-trained models were not fine-tuned during the model training, and no attention mechanism was employed.
To fuse multimodal features effectively, some other researchers proposed to capture interactions between features from different modalities. For example,

- A neural network that leveraged multimodal information was proposed to detect hate speech on social media [23]. A fine-tuned VGG16 model was employed to extract visual features from images, and a 1-D convolutional neural network to extract features from text contents. These features were then optimized by a genetic algorithm to select the better performing subset of features for further model processing. Despite these strengths, the textual context information was not considered to extract during the model training.

- A pre-trained ResNet [24] was proposed to extract visual features from images, and a 1-D convolutional layer was used to extract textual information [25]. Besides, an attention mechanism was proposed to generate better textual context information based on the image features. Then, the features of different modalities were fused together to detect hate speech posts. The weaknesses of this work center on neglecting textual context information in recurrent layers. Also, the text in images was not considered.

- The textual tweet contents and text in images were extracted by a recurrent neural network separately, and the visual features were extracted by a fine-tuned InceptionV3 model [26] from images [27]. Then, the multimodal features were convolved to generate fused features for the model to predict whether the input data contained hate speech content or not. The shortcoming of this study is that the high-level textual context information was not considered to be extracted by more powerful bidirectional recurrent layers, and no attention mechanism was employed in the proposed model.

C. Health Misinformation Detection

Health misinformation on social media has been a subject of particular concern because users seek medical information from social media as opposed to specialized healthcare websites [23]. Although additional efforts are required to check the source credibility, users may not spend a lot of time and energy verifying the source expertise [29]. Some research works have sought to identify the factors that affect the perceived credibility of online health information [30]. Machine learning technologies have been used to identify sources that are credible based on their relationship to professional healthcare sources [31] and their reputation based on followers and shares [32]. For example,

- Machine learning models were developed to track Zika fever misinformation on Twitter [33]. The authors selected the top ten features of Zika fever from a feature set and then built a random decision tree model to classify whether the input tweet is a rumor or not.

- Machine learning models were also proposed to detect health misinformation on Chinese online social media [34]. For the data samples, 75 features that were collected based on specific word frequencies were used as input features. Then, a gradient boosting decision tree model [35] was built to classify whether the input sample is reliable or not.

These methods did not leverage embedding models to vectorize input texts, and the context features among data and hashtag information are overlooked.

D. Antivaccine Detection

Several prior studies have suggested machine-learning approaches to investigate antivaccine messages. For example,

- A linear regression model was trained to classify antivaccine messages on Twitter [11]. After identifying antivaccine tweets, they began to explore the temporal trends, geographic distribution, and demographic correlates of antivaccine attitudes on Twitter.

- Three different clustering algorithms (visualization of similarities, Louvain, and k-means) were used to find and analyze similar antivaccine cases [36]. This approach was able to find shared clinical characteristics from similar antivaccine cases.

- After collecting participants’ attitudes towards the vaccination debate on Twitter, a support vector machine (SVM) [37] was employed in [9] to classify Twitter data and concluded that new interventions are needed to correct misleading vaccination related claims.

- An RNN was trained to detect and analyze antivaccine sentiment clusters on Twitter [10]. They observed profiles of both antivaccine and provaccine accounts. They discovered, for example, that there is a strong link between antivaccine accounts and commercial sites that sell alternative health products.

However, these methods only consider textual information when analyzing vaccine misinformation on social media. Besides, hashtags have not been used in their methods. Moreover, it has been demonstrated that multimodal features can improve predictive performance in various health-related tasks. For instance,

- A stacked deep polynomial network that leverages both magnetic resonance imaging (MRI) data and positron emission tomography (PET) data to detect Alzheimer’s disease [38].

- A convolutional neural network that leverages the movements from patients’ speech, handwriting, and gait to evaluate the Parkinson’s disease [39].

- A deep convolutional neural network that leverages clinical and dermoscopic images and patient metadata to classify the seven-point melanoma checklist criteria and perform skin lesion diagnosis [40].

These methods demonstrated that the performance of multimodal networks outperform all the single-model networks. Accordingly, to detect antivaccine messages, those methods that only consider textual information would be limited in processing social media messages that are increasingly visual and shorter with only hashtags in lieu of lengthy narratives [41].
Fig. 2. The overview architecture of the proposed multimodal network for antivaccine message detection.

E. Motivations

In our study, we alleviate each of the limitations found in the prior studies. The pre-trained models for visual and textual branches are fine-tuned during model training. Attention mechanisms are applied to both visual and textual branches to obtain stronger feature representations. Especially, we leverage multimodal information to our detection of antivaccine posts for its proven effectiveness in detecting health information.

III. METHODOLOGY

A. Model Overview

A multimodal network was proposed to detect antivaccine messages on social media. As illustrated in Fig. 2, the proposed model contained three main branches for independent feature extraction: the hashtag branch, the text branch, and the image branch. The text overlaying the image was extracted by an optical character recognition (OCR) algorithm and was provided as an additional input to the text branch. Moreover, attention mechanisms were employed separately in each component. The three independent, single-modal features were then projected and fused to generate a fused feature. Finally, the three independent, single-modal features and the fused feature were concatenated for the final classification. In the following, we describe the details of each module in the multimodal network and then present an ensemble of the multimodal networks.

B. The Hashtag Branch

Hashtags are used to express the main topic of the post and to spread posts to those interested in the topic [8]. Hashtags can be viewed as keywords for Instagram posts. As indicated in Fig. 1, these hashtags generally have broad meanings individually and do not have rich context information as words in natural English sentences. If a post is related to antivaccine messages, it will often contain hashtags linked to antivaccine information, such as #vaccinefault.

Hashtags have no white space between consecutive words. It is difficult to use a regular word embedding model to get an effective hashtag vector representation because hashtags will trigger the out-of-vocabulary issue. To represent hashtags appropriately, in this paper, we employed the fine-tuned fastText word embedding model to represent hashtags [42]. This model summarizes subword embeddings as word representations if new words cannot be found directly. For example, #vaccineinjury cannot find any vector representation directly from the embedding vocabulary. However, vaccine, injury can be found. Therefore, hashtags will be assigned an embedding vector representation after using the fastText model. After obtaining the vector representation of every hashtag in the post, we used a dense layer with the tanh activation function to generate hidden representation $h^{*}$ on the post’s hashtags:

$$h^{*}_{n} = \text{Dense}(E_{fast}o_{n}, \ n \in [1, N])$$

where $N$ is the number of hashtags in the post. $o_{n}$ is the one-hot encoding representation of the $n$-th hashtag in the caption. $E_{fast}$ is the fine-tuned embedding matrix. The details of fine-tuning are described in Section [V-B]. The summation of all the hashtag representations was then treated as the representation of hashtags of this post:

$$F_{H} = \sum_{n=1}^{N} h^{*}_{n}, \ n \in [1, N]$$

Hashtag information is useful for detecting antivaccine messages, but it is not reliable to conduct antivaccine detection with hashtag information only. There are two straightforward reasons: (1) some hashtags have a neutral attitude such as #vaccine, and both antivaccine and provaccine messages tend to attach this kind of hashtag; (2) antivaccinists may use provaccine hashtags to disturb vaccination supporters or followers. For example, in Fig. 3, both posts contain #provaccine; however, these two posts state antithetical attitudes towards vaccination. Thus, vaccine-related hashtags are useful to identify vaccine-related posts from vaccine-unrelated posts, but we require other information from the caption and image of a post to determine if this post is related to antivaccine or provaccine messages.

C. Attention Mechanisms in the Texts (the SeTa_Att Module)

Attention mechanisms are commonly implemented as neural network model layers. They are used to help the model focus on the important content of the layer input and generate better layer representations as the layer output. To better represent
textual contents in the post, we propose a new attention mechanism called semantic- and task-attention (SeTa) that will enable our model to pay attention to discriminative textual contents based on both semantic-level and task-level information. In the hashtag branch, for semantic-level attention, the new attention mechanism will indicate which hashtags contribute the most to representing the post’s meaning; in contrast, the task-level attention also concerns which hashtags play an essential role in discriminative antivaccine message detection. Thus, the hashtags that contribute the most to expressing the post’s meaning and helping detect antivaccine messages deserve the majority of the attention. The procedure to compute the SeTa-attention weight for hashtags is summarized in Fig. 4.

Firstly, to compute the semantic-level attention, we fed the representation of hashtag $h_n^s$ into a multilayer perceptron (MLP1) to get its corresponding hidden states $u_n^s$:

$$u_n^s = \text{tanh}(W_{H1}h_n^s + b_{H1}), \quad n \in [1, N]$$  \hspace{1cm} (3)

where $W_{H1}$ and $b_{H1}$ are the learnable weight matrix and bias term, respectively. We then computed the semantic importance of the hashtag, $p_n^{SeTa}$:

$$p_n^{SeTa} = u_n^s T h_{ctx}, \quad n \in [1, N]$$  \hspace{1cm} (4)

where $h_{ctx}$ is a learnable context parameter vector.

The task-level attention for hashtag $h_n^s$ is calculated based on its similarity with some popular antivaccine-related hashtags. We collected a set of popular antivaccine-related hashtags (please refer to Section IV-B for details), extracted the feature representations of these hashtags, and then averaged these representations as a single vector, $\overline{h}_{anti}$, to represent the popular hashtags. To compute the similarity between $h_n^s$ and $\overline{h}_{anti}$, we first passed $h_n^s$ through another multilayer perceptron (MLP2) such that the output had the same dimension as $\overline{h}_{anti}$:

$$v_n^h = \text{tanh}(W_{H2}h_n^s + b_{H2}), \quad n \in [1, N]$$  \hspace{1cm} (5)

We then computed the task-level attention of the hashtag, $p_n^{Ta}$, via the similarity between the $n$-th hashtag and the representative antivaccine hashtag $\overline{h}_{anti}$:

$$p_n^{Ta} = v_n^h T \overline{h}_{anti}, \quad n \in [1, N]$$  \hspace{1cm} (6)

The semantic-level and task-level similarities were combined:

$$p_n^{SeTa} = p_n^{Se} + p_n^{Ta}, \quad n \in [1, N]$$  \hspace{1cm} (7)

Then, $p_n^{SeTa}$ was passed through a softmax function to obtain the final attention weight values $\alpha_n^{SeTa}$ for the $n$-th hashtag.

We were then able to compute the vector representation of all the hashtags in the caption with their SeTa-attentions:

$$F_{Hi}^{att} = \sum_{n=1}^{N} \alpha_n^{SeTa} h_n^s, \quad n \in [1, N]$$  \hspace{1cm} (8)

D. The Text Branch

The text branch primarily processes captions and text that overlays the images. Text overlaid on an image can also provide useful information for detecting antivaccine messages. For example, in Fig. 1(a), the words mandate, force, deceive, or threaten those who question it are useful in classifying the post as an antivaccine message. We employed the popular Tesseract OCR algorithm\(^1\) to extract textual content from images. The extracted textual content was concatenated to the caption and then fed into the text branch for further processes, as illustrated in Fig. 2. The texts in the caption or those extracted from OCR consist of sequential natural English words and punctuation. To represent textual contents efficiently, we chose to vectorize texts with the fine-tuned fastText model. Words in the texts are transformed into vector representations by the following embedding matrix:

$$w_t = E_{fast}o_t, \quad t \in [1, T]$$  \hspace{1cm} (9)

where $o_t$ is the one-hot encoding representation of the $t$-th word in a text sequence with $T$ words; and $w_t$ is the corresponding $t$-th word representation in the text. After obtaining the word-level representations, we investigated the sentence-level semantic meaning of each word in the text. A bidirectional RNN with GRU was utilized to catch both the forward and backward context information of each word within the text:

$$\overline{w}_t = [\overline{\text{biGRU}}(w_t); \overline{\text{biGRU}}(w_t)]$$  \hspace{1cm} (10)

where $\overline{\text{biGRU}}(w_t)$ and $\overline{\text{biGRU}}(w_t)$ correspond to forward and backward hidden context states of the $t$-th word in the text, respectively. After obtaining each word’s context representation, we followed the same concept introduced in Section III-C to compute semantic- and task-level attention weights $\beta_n^{SeTa}$ for the text branch. The whole text representation $F_{Ct}^{att}$ could then be represented as:

$$F_{Ct}^{att} = \sum_{t=1}^{T} \beta_n^{SeTa} \overline{w}_t, \quad t \in [1, T]$$  \hspace{1cm} (11)

E. The Image Branch

To extract visual features from images, we used a fine-tuned VGG19 network. The fine-tune details were described in Section IV-B. In this study, we extracted hidden representations $Z_V$ from the last convolutional layer of the fifth convolutional block in the fine-tuned VGG19 network. Attention mechanisms have been proven to be successful in both natural language processing\(^4\) and computer vision.

\(^1\)https://pypi.org/project/pytesseract/
areas [44]. The visual-based attention mechanism usually helps the model pay attention to the important spatial areas of the input feature maps. In the image branch, we employed the idea of concurrent spatial and channel squeeze-and-excitation (scSE) block [45], [46]. The scSE block could help the model pay attention to different areas within feature maps and pay attention to discriminative feature channels. After applying the scSE block on \( Z_V \) to generate spatial-and-channel attention weights \( s_V \), we created the weighted image feature maps:

\[
Z^\text{att}_V = Z_V s_V
\]  

(12)

where \( Z^\text{att}_V \) is the attention-weighted feature map. We then passed this feature map through a global average pooling (GAP) layer [47] to generate the final image feature:

\[
F^\text{att}_V = \text{GAP}(Z^\text{att}_V)
\]  

(13)

The GAP operation reduced feature map dimensions and decreased the total number of parameters in our model.

F. Projection and Fusion Modules

**Feature Projection:** The multimodal features from three branches were in different feature spaces. Directly fusing them by simple operations, such as summation, was not suitable. We proposed a projection module that contained one fully-connected layer with a rectified linear unit (ReLU) activation function to project the features from three branches to the same representation space. The image branch features after the projection can be computed as follows:

\[
F^\text{proj}_V = P_M(F^\text{att}_V)
\]  

(14)

where \( P_M \) denotes the feature project module. Similarly, we obtained the projected caption features \( F^\text{proj}_C \) and projected hashtag features \( F^\text{proj}_H \).

**Feature Fusion:** After obtaining the projected multimodal features, we were able to compute the SeTa attention \( \gamma^\text{ScTa} \) on these features as before. We then combined these weighted features by weighted summation to generate a fused feature \( F^\text{att} \) as follows:

\[
F^\text{att} = \sum_i \gamma^\text{ScTa}_i F^\text{proj}_i, \quad i = [H, C, V]
\]  

(15)

multimodal independent features were concatenated with the fused feature to create the following comprehensive feature:

\[
F = [F^\text{att}_H; F^\text{att}_C; F^\text{att}_V; F^\text{att}_F]
\]  

(16)

G. Classifier

Given the comprehensive feature \( F \), the probability of this message belonging to an antivaccine message or not, \( p(F) \), was able to be predicted by a classifier. In this paper, we built the classifier with three dense layers. During the model training, we used the cross-entropy to compute the loss of the \( k \)-th input message as follows:

\[
\mathcal{L}(F_k) = -[y_k \log(p(F_k)) + (1 - y_k) \log(1 - p(F_k))]
\]  

(17)

where \( k \in [1, K] \) and \( K \) is the total number of input data samples; \( F_k \) is the comprehensive feature of the \( k \)-th message; and \( y_k \) is the ground truth label of the \( k \)-th input message.

H. Ensemble of the multimodal Networks

Ensemble methods leverage multiple models to achieve better testing performance than any single model alone. Ensemble methods have been successfully applied to different detection and classification tasks [48]–[50]. For our task, after the proposed multimodal network was trained, it could be applied in order to test the dataset and made predictions directly. To further improve the model performance, an ensemble method was proposed to employ both single-modal prediction results and multimodal network prediction results. Fig. 5 illustrates the whole ensemble method process, which combines four different model outcomes to generate final predictions. In the figure, the **three-branch model** denotes the proposed multimodal network in this paper; the **visual-based model** denotes the single modal network using images only; the **text-based model** denotes the single modal network using captions only; and the **hashtag-based model** denotes the single modal network using hashtags only. We trained these four models with the same training dataset. For each training data, we first used the multimodal network to obtain a prediction score \(-s_F\); secondly, we used the three single-modal networks to make individual predictions and get three prediction scores \(-s_V, s_C, \) and \( s_H\); thirdly, these four prediction scores were combined as a four-dimensional feature: \((s_F, s_V, s_C, s_H)\). For all the training samples, we acquired their corresponding four-dimensional features. Finally, an SVM model with a radial basis function (RBF) kernel was trained with these four-dimensional features. In the testing phase, for all testing samples, four-dimensional features were generated. These new features were then fed into the trained SVM model to make final ensemble predictions.

IV. EXPERIMENT AND RESULTS

In this section, we introduced a real-world social media dataset collected from Instagram and then presented the experimental implementation details. To evaluate the effectiveness of each component in the proposed model, we tested the proposed model on this dataset and compared the performance with several state-of-the-art models. We then performed ablation studies on several variations of the proposed network. Finally, we conducted an online antivaccine message detection experiment with our proposed model.
A. Dataset

We collected Instagram posts posted from January 2016 to October 2019 using an Instagram API toolkit[^1]. The total number of collected samples included 31,282 Instagram posts that consisted of 50% antivaccine posts and 50% non-antivaccine posts. For the data collection, we adopted a snowballing method widely used for systematic literature reviews[^51]. The first step of snowballing involved searching for posts using various combinations of keywords and hashtags that are commonly found in antivaccine posts on social media[^52],[^53]. Examples of such keywords are #vaccinesafety, #bigpharma, #informedconsent, and #adverseeffects[^52],[^53]. From these search results, we downloaded antivaccine posts. Furthermore, from the search results, we found Instagram accounts that frequently post antivaccine messages and have large numbers of followers. These accounts are representatives of antivaccinists as evidenced by the large numbers of antivaccine messages they post and their large numbers of followers. We found a total of 32 accounts with an average of 8,368 followers per account. These antivaccine accounts include Instagram communities and individual antivaccinists. From these accounts, we downloaded additional antivaccine messages. Non-antivaccine posts included both provaccine posts and vaccine-irrelevant posts and were collected in a similar manner. We first used combinations of known keywords and hashtags, such as #vaccinesaves and #vaccineworks, to find noticeable provaccine accounts. Provaccine posts and vaccine-irrelevant posts were collected from 29 representative accounts. These provaccine accounts included globally or nationally recognizable institutions, such as the Centers for Disease Control (CDC), the World Health Organization (WHO), and Stanford Medical School, in addition to verified doctors. Their known credibility ensures they represent provaccine communities on social media. We engaged three trained annotators to label these posts independently. They then used a majority voting scheme to choose the ultimate labels for the posts without a consensus among the three annotators. For training the proposed model, we randomly split the whole dataset into the training, validation, and testing sets by a 7:1:2 ratio. In other words, 21,000 samples were used as the training set, 3,000 samples were used as the validation set, and the remaining samples were used as our testing samples.

B. Implementation Configurations

The Hashtag Branch: We fine-tuned the pre-trained fastText word embedding model by continuing the model training with auxiliary data samples. The hashtag branch input size was set as 30 because almost no post contains more than 30 hashtags. Moreover, in the SeTa-attention mechanism, based on their frequency, we chose popular hashtags in antivaccine posts on social media reported in a prior study[^56]. Selected examples are #vaccinetruth, #vaccineinjury, #vaccinecauseautism, #vaccineawareness, #fascism, #whistleblower, #bigpharma, and #informedconsent.

[^1]: https://pypi.org/project/InstagramAPI/

The Text Branch: We used the same embedding representation as in the hashtag branch. The text branch input size was set as 680. It was the maximum word length of both captions and OCR results.

The Image Branch: Firstly, we set the fifth convolutional block of the VGG19 network to be trainable and then fine-tuned the pre-trained VGG19 model. The output of the last convolutional layer of the VGG19 model was extracted as the image feature maps with a dimension of $7 \times 7 \times 512$. For the scSE block of the image branch, we used the default value of reduction ratio as 16.

Classifier and Training: After we obtained the multimodal comprehensive features, they were passed through three dense layers with hidden units of 256, 128, and 64, respectively. Each dense layer was followed by a batch normalization layer and a dropout layer. During model training, we chose an RMSprop optimizer with a learning rate from $1 \times 10^{-4}$ to $1 \times 10^{-4}$ with a mini-batch size of 32. Moreover, the proposed model was implemented with Keras, which uses Tensorflow as the backend engine.

C. Quantitative Performance Comparison

In this section, we compare the proposed model to several state-of-the-art models on our dataset. Table I displays the performance of all the compared models in three categories: (1) image-based networks: these models are listed from No. 1 to No. 6 in the table. In our experiment, these models were initialized with weights learned from ImageNet and fine-tuned with our dataset; (2) text-based networks: these models are listed from No. 7 to No. 9 in the table. These three networks were designed based on a recurrent neural network with GRU or long short-term memory (LSTM) units. They were trained from scratch on our dataset; and (3) multimodal based networks: these models are listed from No. 10 to No. 12 in the table, which uses both visual and textual information for the model training. These models were also trained entirely on

| No. | Models          | Accuracy | Precision | Recall | $F_1$ |
|-----|-----------------|----------|-----------|--------|-------|
| 1   | VGG16[^2]       | 0.827    | 0.809     | 0.829  | 0.819 |
| 2   | VGG19[^2]       | 0.829    | 0.822     | 0.812  | 0.817 |
| 3   | ResNet50[^24]   | 0.838    | 0.870     | 0.771  | 0.818 |
| 4   | ResNet101[^24]  | 0.839    | 0.847     | 0.803  | 0.825 |
| 5   | DenseNet121[^54]| 0.833    | 0.866     | 0.761  | 0.810 |
| 6   | DenseNet169[^54]| 0.841    | 0.886     | 0.759  | 0.818 |
| 7   | GRU2[^55]       | 0.884    | 0.877     | 0.875  | 0.876 |
| 8   | GRU1[^55]       | 0.879    | 0.869     | 0.874  | 0.871 |
| 9   | LSTM1[^55]      | 0.846    | 0.861     | 0.803  | 0.831 |
| 10  | att-RNN[^12]    | 0.920    | 0.912     | 0.917  | 0.915 |
| 11  | EANN[^14]       | 0.848    | 0.845     | 0.828  | 0.836 |
| 12  | MVAE[^15]       | 0.929    | 0.936     | 0.929  | 0.933 |
| 13  | three-branch (ours) | 0.966    | 0.969     | 0.957  | 0.963 |
| 14  | ensemble (ours) | 0.974    | 0.978     | 0.967  | 0.973 |
our dataset. The performances of our three-branch multimodal network and its ensemble version are listed in the last two lines of the table.

Based on the testing results in Table I we have several observations: (1) our proposed network outperforms the other multimodal based networks; (2) models that leverage multimodal information perform better than models only considering single modal information. It also validates the multimodal information is important to detect antivaccine posts on social media; (3) text-based models perform better than image-based models. This is reasonable since textual information contains more explicit antivaccine information than visual information in the posts; and (4) the proposed ensemble method improves the model performance.

D. Ablation Study

To evaluate the effectiveness of main components in our multimodal network (three-branch), we conducted more experiments to examine their corresponding performances: (1) ours_noF: this was designed as the proposed multimodal network but without using the fused feature \( F_{\text{feat}} \); (2) ours_noO: this was created as the proposed network without the projection module (i.e., the three multimodal features were leveraged directly); (3) ours_noAtt: all the attention mechanism parts of the proposed network were removed in this variation; (4) ours_noOCR: this was created as the proposed multimodal network without the OCR component; (5) single-modal: we create three single-modal networks. Each of them is one branch of the proposed model. For example, image_only refers to a model that consists of the image branch of the proposed model only; (6) bi-modal: each bi-modal network takes only two branches of the proposed network. For instance, image+caption denotes the model that has both image and text branches of the proposed network but does not include the hashtag branch.

Based on the results in Table II we observe the following: (1) based on the results of No. 0 and No. 1, the fused feature \( F_{\text{feat}} \) has positive effects for antivaccine detection; (2) based on the results of No. 0 and No. 2, the model performance is decreased if there is no projection module; (3) based on the results of No. 0 and No. 3, the proposed model performance benefits from the attention mechanisms. It helps the proposed model improve the testing accuracy from 94.2% to 96.6%. It demonstrates the importance of the proposed attention mechanisms in the model; (4) based on the results of No. 0 and No. 4, the OCR module can improve the model performance slightly because not every post contains text overlaid on the image; (5) results from No. 5a to No. 5c illustrate the single caption branch has better testing performance than the single image branch. The results also demonstrate that the textual information plays a more important role than visual information for our antivaccine detection task; and (6) results from No. 6a to No. 6c indicate that bi-modal networks have better performances than single-modal networks, but bi-modal networks still have the inferior performances compared to our multimodal network that uses all three modalities. It also demonstrates that it is important to leverage all the multimodal information to detect antivaccine posts on social media.

For the proposed ensemble method, given the four prediction scores (i.e., \( s_F \), \( s_V \), \( s_C \), and \( s_H \), as described in Section III-H), the range of each prediction score is \([0, 1]\), 0 denotes non-antivaccine posts, and 1 denotes antivaccine posts. To evaluate the effectiveness of the proposed ensemble method (ensemble), we conducted several additional experiments to compare the performances: (7) ensemble_mean: the mean value of these four scores were computed as the final prediction score; (8) ensemble_max: we first computed the absolute differences between prediction scores and 0.5, then we chose the prediction score that had the maximum absolute difference value as the final prediction score. For example, suppose the four prediction scores for an input post are 0.4, 0.3, 0.35, and 0.9, respectively. The absolute values after subtracting 0.5 are 0.1, 0.2, 0.15, and 0.4. We can thus consider this post as an antivaccine post because its prediction is 0.9, which has the maximum absolute difference value (i.e., 0.4) in this example; (9) ensemble_vote: firstly, we made the predictions based on the four scores individually and then made our final prediction with the majority voting rule. If a tie occurred, we took the mean values of both sides and then chose the one with a maximum deviation from 0.5 as the final prediction result. For example, if the prediction scores are 0.2, 0.3, 0.8, and 0.9, then the corresponding prediction results are 0, 0, 1, and 1, wherein a tie occurs. In this instance, we obtained the mean values of both sides: 0.25 and 0.85. We then acquired the values of deviation from 0.5 (i.e., the absolute difference values from 0.5) as 0.25 and 0.35. We could thus consider this example as an antivaccine post as 0.35 is the maximum deviation value from 0.5 in this example, and the corresponding prediction results are both 1 (i.e., antivaccine).

Based on the results No. 7 to No. 10 in Table II we discovered that the proposed ensemble method achieves a
Fig. 6. Examples of antivaccine posts that are detected successfully by the proposed multimodal network but missed by single-modal networks. Both visual and textual attention mechanism results are illustrated. Red denotes attention weights for both images and texts. The OCR results are illustrated inside black boxes. “Null” denotes that no textual content is detected in the post.

better performance than the other three methods.

E. Qualitative Examples

To illustrate the importance of the multimodal feature fusion to antivaccine message detection, we ran several experiments with the multimodal network and single-modal networks. We analyzed some experimental results that were detected successfully by the proposed multimodal network but missed by single-modal networks. Furthermore, the visualizations of attention mechanisms provided some straightforward explanations for what the proposed model pays attention to when it makes prediction results.

As indicated in Fig. 6(a), we present an example of a post that is detected by the proposed multimodal network but missed by the single image model. The image contains little antivaccine information. However, the caption and hashtags provide deterministic clues to identify the category of this post. Fig. 6(b) displays an example of an antivaccine post that is detected by our multimodal network but missed by the single caption model. The image attached in the post evidently presents an attitude of vaccine suspicion. The OCR results contribute when the model makes a prediction. However, the caption does not state a clear attitude toward vaccination. In Fig. 6(c), an antivaccine post is detected by the multimodal network but missed by the single hashtag model. The post contains two hashtags that are not directly related to antivaccine messages; it thus cannot be recognized by the single hashtag model. However, the proposed multimodal network can obtain reliable clues to make an accurate prediction based on the contents of the image and the caption. Based on these examples, we can also observe that the proposed model, which leverages both visual and textual information, outperforms single-modal networks.

Fig. 7. Examples of testing failure cases when applying the proposed multimodal network. “Null” denotes no hashtags in the post.

F. Failure Case Analysis

As demonstrated in Table I, the proposed model achieved 97.3% F1 score on the Instagram dataset collected from January 2016 to October 2019. This is close to a perfect performance, and it is worth analyzing the failure cases for the future work. Some antivaccine posts contain insufficient information in the images and captions, which are difficult for the proposed model to make correct predictions. As indicated in Fig. 7(a), the post does not contain enough information; only the words on the white mask are relevant. However, the OCR algorithm cannot detect these small, handwritten words correctly. Thus, the proposed model fails to recognize it as an antivaccine post. For some posts, external knowledge is necessary to make correct predictions. For example, in Fig. 7(b), the post is related to rejecting SB792, which concerns child immunization requirements in childcare centers. It is difficult for the proposed model to make correct decisions without the necessary domain knowledge. Moreover, some posts do not contain explicit antivaccine information, as shown in Fig. 7(c). In the picture, only the number of children with autism are illustrated. It is not easy for the model to make correct predictions based only on this post. However, if we read the post exhibited in Fig. 7(d), we understand that antivaccinists believe that there is a relation between vaccines and autism. If the model can infer the context relations among posts and be embedded with the domain knowledge from human experts, this will improve the model performance.

G. Online Antivaccine Message Detection

To evaluate the antivaccine message detection ability of the proposed network, we applied the proposed multimodal network on Instagram to detect antivaccine posts for one month (2019/11/01–2019/11/30). The same hashtags that were reported in Section IV-A were used to search for daily posts that are related to vaccine, antivaccine, or provaccine messages. We then applied the proposed multimodal network

3http://www.sdiz.org/documents/Sch-CC/sb792_factsheet_adapted.pdf
feasibility of the proposed network for antivaccine misinformation detection on social media.

However, the proposed model still has some limitations when the model is applied to antivaccine posts without sufficient context information. Moreover, the model cannot make correct predictions when human domain knowledge is necessary. For future works, we will consider adding memory cells to force the model to remember some essential features during the model training phase. The memory cells can help the model build connections among different training samples and correctly make predictions for difficult testing cases.

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