Detection of Propaganda Techniques in Visuo-Lingual Metaphor in Memes

Sunil Gundapu
Language Technologies Research Centre
KCIS, IIIT Hyderabad
Telangana, India
sunil.g@research.iiit.ac.in

Radhika Mamidi
Language Technologies Research Centre
KCIS, IIIT Hyderabad
Telangana, India
radhika.mamidi@iiit.ac.in

Abstract

The exponential rise of social media networks has allowed the production, distribution, and consumption of data at a phenomenal rate. Moreover, the social media revolution has brought a unique phenomenon to social media platforms called Internet memes. Internet memes are one of the most popular contents used on social media, and they can be in the form of images with a witty, catchy, or satirical text description. In this paper, we are dealing with propaganda that is often seen in Internet memes in recent times. Propaganda is communication, which frequently includes psychological and rhetorical techniques to manipulate or influence an audience to act or respond as the propagandist wants. To detect propaganda in Internet memes, we propose a multimodal deep learning fusion system that fuses the text and image feature representations and outperforms individual models based solely on either text or image modalities.

1 Introduction

Memes are usually an image superimposed with a text description and are used to express a range of ideas such as humour, embarrassment, hate, propaganda, and even more emotions. The word meme was introduced by Dawkins [1976], and initially, it refers to an idea, behaviour, or style that disseminates from person to person within a culture. With the growth of the social network community, the participation of memes on online social networks has increased tremendously in recent years. In the age of the internet, it has been adopted to refer to a part of the culture, typically a joke, rumour, or catchphrase, which gains influence through online transmission [Davison, 2012]. They spread among people using social media platforms, blogs, instant messaging applications, emails, and forums in their simplest form. Content-wise, they usually include unconventional news, dialogues, catchlines, images, or videos.

According to Nieubuur [2021], Internet memes are one of the more popular contents used in online disinformation campaigns. An essential aspect of a problem that is often overlooked in social media platforms is the mechanism through which false information is being communicated, which is utilising propaganda techniques. These techniques are deliberately designed communication that invites people to respond emotionally, immediately, and in one way or another. These were initially high on advertising and public relations, news and journalism, politics, entertainment but are now appearing on all aspects of daily life, and more importantly on social media platforms.

Propaganda techniques comprise of psychological and rhetorical strategies, ranging from logical fallacies — such as black-and-white fallacy (present only two possibilities among many), straw man (misconstrue person’s actions or opinion), red herring (introduce irrelevant data to distract), and whataboutism — to influencing audience emotions — such as using slogans, loaded language, appeal to authority, flag-waving, and clichés. Identifying logical fallacies is challenging because, at first glance, the argument may seem correct and objective. However, we can spot them through careful
observation and analysis. Another set of techniques use emotional language to motivate the viewer to accept the speaker only based on the emotional bond being created, which will stop any rational analysis of the argument.

In recent times, propagandists are generating Internet memes by using propaganda techniques to influence viewers or readers to believe in someone or something. American scientist Robert Peter W. Singer describes in his book “LikesWar” that social media propaganda and misinformation are emerging as a new weapon in the modern warfare. Therefore, it is essential to find out propaganda campaigns in Internet memes to stop spreading them. So, in this paper we aims to build a multimodal fusion system that can identify the Internet memes in which propaganda techniques are used. The system takes pair (text, image) of an Internet meme as an input to determine which of the propaganda techniques is used in the text and visual content of the meme.

2 Related Work

Evolution of Propaganda: Propaganda techniques are not new. The term propaganda was used in the early 17th century and was first used to propagate Catholic beliefs and practices in the New World and later to manipulate people in public gatherings such as festivals, games, and theaters [ASamuel C Woolley and Philip N Howard, 2018]. But in the present technological world, this propaganda has progressed to computational propaganda [Bolsover and Howard, 2017b], where information is dispensed through technology such as social media platforms so that it is possible to reach well-targeted communities at high speeds. This propaganda shared on these platforms can be text, visual or text-vision combinations. Internet memes are critical in spreading multimodal propaganda on social media platforms [DiRESTA, 2018]. The present social media ecosystem and virality bots allow memes to spread effortlessly, switching from one target group to another. Currently, efforts to curb the spread of such memes are focused on analyzing social media networks and searching for fake accounts and bots to lessen the spread of such content [Cresci et al., 2017, Yang et al., 2019b].

Propaganda in Text Modality: In the natural language processing community, much research is done on propaganda by analyzing textual content [Barrón-Cedeño et al., 2019, Rashkin et al., 2017, Martino et al., 2019]. Rashkin et al. [2017] studied the propaganda at document level by creating TSHP-17 dataset. This dataset developed with the help of English Gigaword corpus and labelled with four classes: satire, trusted, hoax, and propaganda. On this dataset, they trained a logistic regression model with n-gram level word representations. To analyze the propaganda at sentence level [Barrón-Cedeño et al., 2019] developed a new QProp dataset with two labels: propaganda, and non-propaganda. On this binary labeled corpora they trained various machine learning models like logistic regression, SVMs to discriminate propaganda from non-propaganda datapoints.

In a similar fashion, Habernal et al. [2017] created a dataset with 1300 data points with five propaganda beliefs, including irrelevant authority, ad hominem, and red herring, which are directly associated with propaganda techniques. Martino et al. [2019] examines the propaganda at the fragment level. For this, they created a PTC dataset by annotating the news articles with 18 propaganda techniques. There are two types of experiments done on this dataset. The first one is a two-class classification: Whether the given input news article using any of 18 techniques or not. Another task is multi-label classification and span detection: For the input text, find the span of text fragments where the propaganda techniques are used and identify the type of propaganda technique. Recently, Martino et al. [2020] on detection of computational propaganda from the perspective of NLP and Network Analysis mentioned the need for collective efforts between these communities. There is also a dedicated Big Data Journal on Political Big Data and Computational Propaganda [Bolsover and Howard, 2017a].

Propaganda in Multimodality: Originally, propaganda campaigns have appeared in text modality, but nowadays, they appear in every possible modality. Propaganda techniques are more accessible to spot in text modality than multimodalities such as memes because contextual information related to the propaganda can be included in more than one of the multiple modalities.

To understand aspects of visual propaganda, Seo [2014] analyzes the social media tweet images posted by the Hamas’ Alqassam Brigades and Israel Defense Forces during the 2012 Gaza conflict. By selecting 10 Youtube videos, Abd Kadir et al. [2016] studied the comprehend relationships between

---

1https://knowledge.wharton.upenn.edu/article/singer-weaponization-social-media/
these videos and propaganda techniques and people’s emotions. Simultaneously they analyze how these videos are influencing people’s emotions with the help of propaganda techniques.

Volkova et al. [2019] prepared a dataset with 50K twitter posts consisting of memes annotated with six labels: propaganda, disinformation, hoaxes, clickbait, conspiracies, and satire. They developed a multimodal approach for this problem by considering the textual, linguistic characteristics, and visual features. Glenski et al. [2019] proposed two classification tasks to explore the multilingual content for deception detection. Both tasks are intended to identify the category of a social media post, but the first task has four output categories (propaganda, conspiracy, hoax, or clickbait), and the second task has five output categories with an extra category of disinformation.

Some quality works done on multimodality content before this propaganda problem, such as the spread of false information [Dupuis and Williams, 2019], hateful memes identification [Kiela et al., 2020], [Lippe et al., 2020], [Das et al., 2020], [Gundapu and Mamidi, 2020], antisemitism [Chandra et al., 2021].

Multimodal Models and Fusion Techniques: Facebook Hateful Memes Challenge has been very helpful in developing different types of multimodal models and to fine-tune the state-of-art multimodal transformer models such as ViLBERT [Lu et al., 2019], Multimodal Bitransformers [Kiela et al., 2020], and VisualBERT [Li et al., 2019]. And also Vidgen et al. [2019] pointed that memes make perfect sense when both text and image content are taken into account. By considering this point, many authors [Baltrusaitis et al., 2019] [Yang et al., 2019a] [Gallo et al., 2018] have explored different multimodal fusion strategies to combine modalities.

### 3 Dataset

In this paper, we predominately focused on the task of propaganda techniques identification in Internet memes. We formulated this task as a multi-label classification problem because each input is labeled with more than one propaganda technique. We took the dataset from the 15th International Workshop on Semantic Evaluation (SemEval-2021) for this task [Dimitrov et al., 2021]. The dataset comprises of 950 pair (text, image) of social media posts, and each pair labeled with propaganda techniques. In the input pair (text and image), the text is extracted from the meme using OCR, and the image is a meme. We used 22 propaganda techniques for our task and put them in Table 1. A more detailed list of propaganda techniques with definitions and examples is available online and in appendix, we are adding few meme examples.

This dataset contains 687 pairs of data points for model training, 63 data points for model hyperparameter tuning, and 200 data points for model testing. Table 1 shows the proportion of propaganda techniques in the train, valid, and test sets.

| Propaganda Techniques | Train | Dev | Test |
|-----------------------|-------|-----|------|
| Appeal to Emotions    | 68    | 3   | 19   |
| Appeal to authority   | 19    | 3   | 13   |
| Bandwagon             | 62    | 0   | 34   |
| Black-and-white       | 33    | 1   | 33   |
| Fallacy               | 16    | 0   | 17   |
| False          | 35    | 0   | 31   |
| Load     | 32    | 0   | 31   |
| Loaded  | 36    | 0   | 30   |
| Language             | 36    | 0   | 36   |
| Name Calling          | 32    | 0   | 32   |
| Obfuscation           | 35    | 0   | 32   |
| Red Herring           | 32    | 0   | 31   |
| Retardation           | 31    | 0   | 31   |
| Reductio ad hitlerum  | 32    | 0   | 32   |
| Repetition            | 30    | 0   | 30   |
| Smear                | 31    | 0   | 32   |
| Thought-endig cliché  | 31    | 0   | 31   |
| Whataboutism          | 30    | 0   | 30   |

Table 1: List of propaganda techniques and their count in train, development, and test sets.

---

[https://propaganda.math.unipd.it/semeval2021task6/definitions22.html](https://propaganda.math.unipd.it/semeval2021task6/definitions22.html)
4 Proposed Approaches

Individual Modality Models: In the beginning, we started to examine our task, “Identification of propaganda techniques in Internet memes,” with individual modalities (text or image). For text data, we have developed various Machine Learning (ML) and Deep Learning (DL) models with different word embeddings. Nevertheless, BERT and RoBERTa gave superior results for this textual modality than the ML and DL models with the Glove [Pennington et al., 2014] and FastText [Bojanowski et al., 2016] embeddings. On the image data, we experimented with CNN and pre-trained image classification models. Pre-trained models gave significantly better results than traditional CNN models. And when comparing the results of individual modalities, text modality models gave more effective results than image modality models. This is because there is more information about the propaganda in the textual data than in the visual data in the memes.

Cross-Modality Multimodal Models: After analyzing the results of individual modalities, we started to fine-tune cross-modality by multimodal (Vision-and-Language) pretraining models like UNITER [Chen et al., 2019], ViLBERT [Lu et al., 2019], and VisualBERT [Li et al., 2019], and these pre-trained models performed better than individual modality models. Following individual and cross-modality models, we explored multimodal fusion approaches to combine information from text and vision input modalities in a principled way.

4.1 Multimodal Fusion System

In a multimodal fusion setting, ML/DL models are trained on separate modalities and integrated simultaneously. When individual modality features are merged into output layers, this is called Late Fusion. On the other hand, there is an inversion of late fusion called Early Fusion to fuse modalities. In this fusion, features are incorporated at the input level before being given in the model. We experimented on our task by fusing text encoder (encodes text data) and image encoder (encodes the image data) using early fusion and late fusion methods. After observing the results of these methods, merging modalities at their individual deepest (or early stage) attributes is not mandatorily the most appropriate way to solve our propaganda identification multimodal task.

In our work, we used an idea “MFAS: Multimodal Fusion Architecture Search” of considering features collected from the hidden layers of individual modalities that could effectively enhance performance with respect to only utilising a single fusion of late (or early) features. Figure 1 describes the structure of our proposed multimodal fusion system for propaganda techniques identification in Internet memes with RoBERTa text encoder, pre-trained VGG-19 image encoder, and multimodal fusion architecture search [Pérez-Rúa et al., 2019] module.

![Figure 1: Multimodal Fusion Architecture](image-url)
Given a pair (text and image) for a social media post, we make use of Transformer based models to encode the text extracted from the Internet meme. We use the pre-trained image classification models to encode the image. Further, the MFAS module fuses the text and image encodings. Next, the fused encodings are transformed using a fully connected network to identify the propaganda techniques. The complete model is trained end-to-end utilising back-propagation. The principal motive of fine-tuning the pre-trained models on the datasets for our multimodal classification task is that our datasets are small. Below we describe each module in the architecture in detail.

4.2 Text Preprocessing

1. **Conversion of chat contractions**: Chat words/phrases are widely used on social networks to express emotions and are very helpful in identifying context. We have created a word contractions dictionary with 250 chat words to convert these chat words to their complete form. Examples: YOLO → you only live once, ASAP → as soon as possible.

2. **URLs removal**: The OCR extracted text consists of URLs like memegenerator.net, etc. We removed those links since they do not give any vital information.

3. **Conversion of elongated words**: With the help of regular expressions, transformed the elongated words to their original form. Examples: Nooooo → No, suuupperrr → super.

4. Using ekphrasis [Baziotis et al., 2017] library, normalizes the time, date, and numbers into a standard format. This library does hashtag splitting and spelling correction. We removed the non-alpha-numeric characters, punctuation marks, and non-ASCII glyphs from the text data.

4.3 Text Encoder

The preprocessed text data tokenized and then forwarded to the text encoder module. We tried the BERT [Devlin et al., 2019], XLNet [Yang et al., 2019c], and RoBERTa [Liu et al., 2019] pre-trained transformer models in the text encoder module to encode the text because they have been shown to give incredible results in multiple NLP classification tasks.

BERT (Bidirectional Encoder Representations from Transformers) employs a multi-layer bidirectional transformer encoder to learn deep hidden bidirectional representations. It has self-attention layers that perform self-attention on input text from both directions. This technique allows the BERT model to know the context of a word in the sentence based on the words around it. We used the BERT base case model for our task, pre-trained on the large unlabeled Book corpus and the entire Wikipedia.

RoBERTa makes use of Transformer [Vaswani et al., 2017], and it is a robustly optimized approach for pretraining NLP models that improve on BERT. RoBERTa was trained with more data, more iterations, larger batch sizes, and learning rates than the BERT. And it eliminates the next-sentence pretraining objective task from the BERT model to boost the training procedure and introduces a new idea in its architecture called dynamic masking. In this idea, masked tokens will change during the model training. For our task, we used the RoBERTa base model.

XLNet is a bidirectional transformer autoregressive model that uses a better training methodology and a more extensive dataset to achieve better results than BERT. In pretraining, it integrates the following two techniques: (1) State-of-the-art Autoregressive model and (2) Transformer XL. Furthermore, XLNet presents a permutation language modeling technique to predict all tokens in random order instead of sequential order. This idea helps the XLNet learn bidirectional relationships among words and handle the dependencies.

For better contextual encodings, we experimented on text data with the above explained three transformer models. However, the RoBERTa gave slightly better results than the BERT and XLNet.

4.4 Image Encoder

In our dataset, input images (memes) are in different shapes and sizes. So before forwarding to any CNN model, we resize all the images to $224 \times 224$ dimensions. After this step, applied few image transformation techniques like rotation, flipping, and cropping on the scaled dataset. We extracted image representations twice from the image encoder. The first step collected the representations from the second last output layer of the CNN model and then fused them with text encodings. Next, image encoder final layer outputs concatenated with text encodings and previous step fused encodings.
An image encoder experimented the various pre-trained CNN architectures like: VGG-19 [Simonyan and Zisserman, 2015], InceptionV3 [Szegedy et al., 2016], Resnet-152 [He et al., 2016], DenseNet-161 [Huang et al., 2017], and InceptionResNetV2 [Szegedy et al., 2017]. Among all these pre-trained models VGG-19 and Resnet-152 gave considerable results for our task.

4.5 Fusion Module

To join the representations procured from the text encoder and image encoder modules, T, F’, and I, we examine with various techniques: (i) Concatenation of both modalities output representations, (ii) Early and Late Fusion, and (iii) MFAS.

Early Fusion: Initially started with a widely used state-of-the-art early fusion technique to fuse both modalities. Early fusion technique (See figure 2) is also known as feature-level fusion technique, which concatenates the embeddings from text and image modalities as input representations for classifiers. This technique can be conveyed as follows:

$$X_{early} = f(U_1, \ldots, U_m, V_1, \ldots, V_n)$$

Here an aggregated representation of the $X_{early}$ attributes is calculated by the function $f$ that connects the individual attributes.

Late Fusion: After early fusion, we experimented with the decision-level late fusion technique (See figure 2). This technique fuses the output level representations of text and image encoder and computes a late fusion score for classifiers. Late fusion technique can be conveyed as follows:

$$X_{late} = g(f_1(U_1), \ldots, f_m(U_m), f_{m+1}(V_1), \ldots, f_{m+n}(V_n))$$

Here functions $f_1, \ldots, f_{m+n}$ are applied to each individual attribute and function $g$ is used to integrate every individual decision by $f_1, \ldots, f_{m+n}$.

Multimodal Fusion Architecture Search (MFAS): Next examined a model-level fusion technique called MFAS, which is a compromise between the two modalities. It concatenates the hidden layer representations from different modalities. As shown in model architecture (figure 1), on our task, this technique initially concatenates the text encoder output representations (T) with image encoder intermediate hidden layer representations (H) then applies a non-linearity sigmoid function.

$$F' = \sigma(T \oplus H)$$

Next, it fuses the output (F’) with text predictions (T) and image predictions (I) along with a non-linearity sigmoid function (F).

$$F = \sigma(T \oplus F' \oplus I)$$
4.6 Classifier

Followed by the fusion model, we have constructed a fully connected network that takes the input from the fusion model. The fully connected network consists of two dense layers with hidden unit sizes of 768 and 384 and finally the output layer with a size of 22 output units has a sigmoid function.

5 Experiments and Results

This experiments section explains model implementation details, hyper-parameter tuning, results of individual text and image modalities classifiers and multimodal + fusion classifiers.

5.1 Hyper-parameter Settings and Implementation Details for Reproducibility

The following experimental settings are used for our work. We trained all the models using the train set and used the validation dataset to find the right set of hyper-parameters. We experimented with different image encoder intermediate layer outputs to get better results. However, Block-2 output ($H$) gave the best results for our work as compared to other blocks’ output.

For all the experiments, we used the Adam optimization algorithm. To increase the model speed and performance, used dropout layers with the probability of 0.2. In the dense layers used the ReLU activation function. And, we used PyTorch [Paszke et al., 2019] and Keras [Chollet et al., 2015] frameworks for building deep learning models, scikit-learn [Pedregosa et al., 2011] for ML models. To fine-tune the transformer models used the PyTorch-based HuggingFace transformer library.

| Modality       | Approach                             | Precision | Recall | F1-Score |
|----------------|--------------------------------------|-----------|--------|----------|
| Only Text      | FastText with LSTM                   | 0.5809    | 0.4679 | 0.5183   |
|                | Glove + BiLSTM + Attention           | 0.5910    | 0.4702 | 0.5237   |
|                | BERT with Dense                      | 0.5958    | 0.4780 | 0.5295   |
|                | XLNet with Dense                     | 0.5936    | 0.4738 | 0.5270   |
|                | RoBERTa with Dense                   | **0.6004**| 0.4901 | **0.5363**|
| Only Image     | Inception-V3                         | 0.4868    | 0.4571 | 0.4841   |
|                | Resnet-152                           | **0.5062**| 0.4618 | 0.4925   |
|                | VGG-19                               | 0.4989    |        |          |
| Cross-Modality | UNITER                               | 0.5841    | 0.4986 | 0.5288   |
|                | ViLBERT                              | 0.5892    | 0.5002 | 0.5348   |
|                | VisualBERT                           | **0.5965**| 0.5034 | **0.5404**|
| Text and Image | Concatenation                        | 0.5684    | 0.4576 | 0.4983   |
|                | Early Fusion                         | 0.5703    | 0.4693 | 0.5058   |
|                | Late Fusion                          | 0.6016    | 0.5076 | 0.5407   |
|                | MFAS                                 | **0.6214**| **0.5077**| **0.5698**|

Table 2: Comparison of various modalities classifiers results

5.2 Results and Analysis of Individual Modalities Classifiers

We started experiments for both (text and image) modalities with ML algorithms and TF-IDF word vectors for baseline model results. After that, we experimented on text modality with five well-known pre-trained text embedding-based classifiers and three pre-trained CNN-based image classifiers. We used Glove, FastText, BERT, XLNet, and RoBERTa for the individual text classification. And we used the VGG-19, InceptionV3, Resnet-152, Densenet-161, InceptionResNetV2 for image classification.

The comparative f1-scores of individual modalities are presented in Table 2. After observing the classification results of individual modalities, we made the following observations:

- Text modality classifiers gave encouraging results, but the image modality classifiers provide lesser f1-scores. We suspect this because images related to propaganda techniques are
usually news articles, memes, or screenshots (sometimes) that generally do not convey any spatial information.

- Among text modality classifiers, Transformer based approaches worked better than the shallow word embedding methods like Glove and FastText. Transformer-based BERT, XLNet, and RoBERTa gave superior results on our task. However, RoBERTa model score surpassed BERT and XLNet models. Among the image modality classifiers, pre-trained VGG-19 gave better results than other pre-trained models.

5.3 Results and Analysis of Multimodal Fusion Classifiers

In this section, we presented results and analysis of various fusion approaches for our proposed multimodal classifier. Based on the results of individual modalities (in Table 2), we noticed that transformer-based RoBERTa is the best text encoder and VGG-19 is the best image encoder for our dataset. Therefore, we did multimodal fusion experiments with these two encoders only. We presented the results of this multimodal classifier with different fusion techniques in Table 2. Moreover, we compared the results of our proposed multimodal system with individual and cross-modality models.

- All the proposed multimodal fusion models for our task performed better than other models by a considerable margin. Cross-modality by pre-training multimodal models are much better than individual modality models. And these models are working best when the visual information in the memes is not covered by textual information.
- In the multimodal late fusion architecture, the Image encoder gives only prediction-level features that do not capture complex information, such as semantic concepts of faces, animals, trees, etc. Due to this, when we concatenate image encodings with text encodings, it sometimes misleads the fusion model outputs.
- Concatenation of encoders features technique and early fusion technique does not meet the expectations. They only give the approximate individual image modality model results.
- Decision level late fusion and MFAS approaches efficiently fused the spatial information from images and semantic information from text and performed better than all other multi-modal systems. However, MFAS multimodal system outperforms the late fusion approach.

6 Error Analysis

For our task, we mostly lean towards pre-trained models because our dataset is tiny. Transformer-based models performed very well on our task and gave considerable results than we expected. However, in some cases, transformer models are incorrectly predicted when the input text length is short. Furthermore, pre-trained CNN classification models were mainly confused for our task in the following contexts to extract vital spatial image information. (i) Few memes are designed with the clubbing of multiple images. In this case, pre-trained models are stumbled to gather information from them. (ii) Some users take screenshots of memes posted by other users and post them again on social media. Lack of additional contextual information in such posts systems making false predictions. (iii) Sometimes, the entire meme is covered with text, making it difficult for CNN models to recognize spatial features in images.

We have analyzed that combining encoder representations from multiple modalities can help identify propaganda techniques in memes. Though, in some cases, we realize that noise in one modality leads to a total misclassification. While doing experiments, we observed that the dataset used for our task has severe class imbalance due to the heterogeneous frequency of various types of propaganda techniques in real life. “Bandwagon, Reduction ad Hitlerum”, “Appeal to Authority”, “Black and White Fallacy”, “Whataboutism, StrawMen, RedHerring”, and “Thought Terminating Cliche” classes samples are significantly less in the dataset compare to other classes samples. To tackle this class imbalance problem, we explored with different data under/over sampling techniques like SMOTE [Chawla et al., 2002], Tomek Links [Tomek, 1976], Near Miss [Zhang and Mani, 2003] for textual data, tried the position and colour augmentation techniques [Perez and Wang, 2017] for image data. Also we used the class weight [Guo et al., 2008] approach which give different weights to both the majority and minority classes. Experimented with an enhanced version of Cross-Entropy Loss that is focal loss [Lin et al., 2017] that seeks to manage the problem of class imbalance by assigning more weight to rough or easily misclassified samples and to low-weight easy samples.
7 Conclusion and Future Work

In this work, we first provided a systematic study on the problem of identification of propaganda techniques in Internet memes. After that, we explored this problem with a multimodal fusion architecture. In this architecture, with the help of the MFAS technique, we fused the text features extracted using RoBERTa model and image features using pre-trained VGG-19. We examined our problem with single modality as well as multimodality classifiers and noticed that fusing features from various modalities enhance the performance. Our multimodal fusion approach achieves 0.5698 micro f1-score on the test data, which is a considerable result. We hope these results will accelerate further research works in this direction.

References

S. Abd Kadir, A. Lokman, and T. Tsuchiya. Emotion and techniques of propaganda in youtube videos. Indian Journal of Science and Technology, Vol (9):1–8, 12 2016. doi: 10.17485/ijst/2016/v9iS1/106841.

ASamuel C Woolley and Philip N Howard. Computational propaganda: political parties, politicians, and political manipulation on social media. Oxford University Press, 2018.

T. Baltrusaitis, C. Ahuja, and L.-P. Morency. Multimodal machine learning: A survey and taxonomy. IEEE Transactions on Pattern Analysis and Machine Intelligence, 41:423–443, 2019.

A. Barrón-Cedeño, I. Jaradat, G. Martino, and P. Nakov. Proppy: Organizing the news based on their propagandistic content. Information Processing & Management, 56, 05 2019. doi: 10.1016/j.ipm.2019.03.005.

C. Baziotis, N. Pelekis, and C. Doulkeridis. Datastories at sensemeval-2017 task 4: Deep lstm with attention for message-level and topic-based sentiment analysis. In Proceedings of the 11th International Workshop on Semantic Evaluation (SemEval-2017), pages 747–754, Vancouver, Canada, August 2017. Association for Computational Linguistics.

P. Bojanowski, E. Grave, A. Joulin, and T. Mikolov. Enriching word vectors with subword information. arXiv preprint arXiv:1607.04606, 2016.

G. Bolsover and P. Howard. Computational propaganda and political big data: Moving toward a more critical research agenda. Big Data, 5:273–276, 12 2017a. doi: 10.1089/big.2017.29024.cpr.

G. Bolsover and P. N. Howard. Computational propaganda and political big data: Moving toward a more critical research agenda. Big data, 5 4:273–276, 2017b.

M. Chandra, D. Pailla, H. Bhatia, A. Sanchawala, M. Gupta, M. Shrivastava, and P. Kumaraguru. “subverting the jewtocracy”: Online antisemitism detection using multimodal deep learning. pages 148–157, 06 2021. doi: 10.1145/3447535.3462502.

N. Chawla, K. Bowyer, L. Hall, and W. P. Kegelmeyer. Smote: Synthetic minority over-sampling technique. J. Artif. Intell. Res., 16:321–357, 2002.

Y.-C. Chen, L. Li, L. Yu, A. E. Kholy, F. Ahmed, Z. Gan, Y. Cheng, and J. Liu. Uniter: Learning universal image-text representations. ArXiv, abs/1909.11740, 2019.

F. Chollet et al. Keras, 2015. URL https://github.com/fchollet/keras.

S. Cresci, R. Pietro, M. Petrocchi, A. Spognardi, and M. Tesconi. The paradigm-shift of social spambots: Evidence, theories, and tools for the arms race. 04 2017. doi: 10.1145/3041021.3055135.

A. Das, J. S. Wahi, and S. Li. Detecting hate speech in multi-modal memes. ArXiv, abs/2012.14891, 2020.

P. Davison. The Language of Internet Memes, pages 120–134. 01 2012. ISBN 0814764061.

R. Dawkins. The Selfish Gene. Oxford University Press, 1976.
J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. In *NAACL-HLT*, 2019.

D. Dimitrov, B. B. Ali, S. Shaar, F. Alam, F. Silvestri, H. Firooz, P. Nakov, and G. D. S. Martino. Semeval-2021 task 6: Detection of persuasion techniques in texts and images. *arXiv preprint arXiv:2105.09284*, 2021.

R. DiResta. Computational propaganda: If you make it trend, you make it true. *The Yale Review*, 106(4):12–29, 2018. doi: https://doi.org/10.1111/yyrev.13402. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/yyrev.13402.

M. Dupuis and A. Williams. The spread of disinformation on the web: An examination of memes on social networking. 2019 *IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI)*, pages 1412–1418, 2019.

I. Gallo, A. Calefati, S. Nawaz, and M. K. Janjua. Image and encoded text fusion for multi-modal classification. 2018 *Digital Image Computing: Techniques and Applications (DICTA)*, pages 1–7, 2018.

M. Glenski, E. Ayton, J. Mendoza, and S. Volkova. Multilingual multimodal digital deception detection and disinformation spread across social platforms. *ArXiv*, abs/1909.05838, 2019.

S. Gundapu and R. Mamidi. Gundapusunil at SemEval-2020 task 8: Multimodal memotion analysis. In *Proceedings of the Fourteenth Workshop on Semantic Evaluation*, pages 1112–1119, Barcelona (online), Dec. 2020. International Committee for Computational Linguistics. URL https://www.aclweb.org/anthology/2020.semeval-1.147.

X. Guo, Y. Yin, C. Dong, G. Yang, and G. Zhou. On the class imbalance problem. In *2008 Fourth International Conference on Natural Computation*, volume 4, pages 192–201, 2008. doi: 10.1109/ICNC.2008.871.

I. Habernal, R. Hannemann, C. Pollak, C. Klamm, P. Pauli, and I. Gurevych. Argotario: Computation-argumentation meets serious games. 07 2017.

K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. 2016 *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 770–778, 2016.

G. Huang, Z. Liu, and K. Q. Weinberger. Densely connected convolutional networks. 2017 *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2261–2269, 2017.

D. Kiela, H. Firooz, A. Mohan, V. Goswami, A. Singh, P. Ringshia, and D. Testuggine. The hateful memes challenge: Detecting hate speech in multimodal memes. *ArXiv*, abs/2005.04790, 2020.

L. H. Li, M. Yatskar, D. Yin, C.-J. Hsieh, and K.-W. Chang. Visualbert: A simple and performant baseline for vision and language. *ArXiv*, abs/1908.03557, 2019.

T.-Y. Lin, P. Goyal, R. B. Girshick, K. He, and P. Dollár. Focal loss for dense object detection. 2017 *IEEE International Conference on Computer Vision (ICCV)*, pages 2999–3007, 2017.

P. Lippe, N. Holla, S. Chandra, S. Rajamanickam, G. Antoniou, E. Shutova, and H. Yannakoudakis. A multimodal framework for the detection of hateful memes, 12 2020.

Y. Liu, M. Ott, N. Goyal, J. Du, M. Joshi, D. Chen, O. Levy, M. Lewis, L. Zettlemoyer, and V. Stoyanov. Roberta: A robustly optimized bert pretrained approach. *ArXiv*, abs/1907.11692, 2019.

J. Lu, D. Batra, D. Parikh, and S. Lee. Vilbert: Pretraining task-agnostic visiolinguistic representations for vision-and-language tasks. In *NeurIPS*, 2019.

G. D. S. Martino, S. Yu, A. Barrón-Cedeño, R. Petrov, and P. Nakov. Fine-grained analysis of propaganda in news articles. In *EMNLP/IJCNLP*, 2019.
G. D. S. Martino, S. Cresci, A. Barrón-Cedeño, S. Yu, R. D. Pietro, and P. Nakov. A survey on computational propaganda detection. In IJCAI, 2020.

J. T. Nieubuurt. Internet memes: Leaflet propaganda of the digital age. Frontiers in Communication, 5:116, 2021. ISSN 2297-900X. doi: 10.3389/fcomm.2020.547065. URL https://www.frontiersin.org/article/10.3389/fcomm.2020.547065.

A. Paszke, S. Gross, F. Massa, A. Lerer, J. Bradbury, G. Chanan, T. Killeen, Z. Lin, N. Gimelshein, L. Antiga, A. Desmaison, A. Kopf, E. Yang, Z. DeVito, M. Raison, A. Tejani, S. Chilamkurthy, B. Steiner, L. Fang, J. Bai, and S. Chintala. Pytorch: An imperative style, high-performance deep learning library. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett, editors, Advances in Neural Information Processing Systems 32, pages 8024–8035. Curran Associates, Inc., 2019. URL http://papers.neurips.cc/paper/9015-pytorch-an-imperative-style-high-performance-deep-learning-library.pdf.

F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. Journal of Machine Learning Research, 12:2825–2830, 2011.

J. Pennington, R. Socher, and C. D. Manning. Glove: Global vectors for word representation. In Empirical Methods in Natural Language Processing (EMNLP), pages 1532–1543, 2014. URL http://www.aclweb.org/anthology/D14-1162.

L. Perez and J. Wang. The effectiveness of data augmentation in image classification using deep learning. ArXiv, abs/1712.04621, 2017.

J.-M. Pérez-Rúa, V. Vielzeuf, S. Pateux, M. Baccouche, and F. Jurie. Mfas: Multimodal fusion architecture search. 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 6959–6968, 2019.

H. Rashkin, E. Choi, J. Jang, S. Volkova, and Y. Choi. Truth of varying shades: Analyzing language in fake news and political fact-checking. pages 2931–2937, 01 2017. doi: 10.18653/v1/D17-1317.

H. Seo. Visual propaganda in the age of social media: An empirical analysis of twitter images during the 2012 israeli–hamas conflict. Visual Communication Quarterly, 21:150–161, 07 2014. doi: 10.1080/15551393.2014.955501.

K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. CoRR, abs/1409.1556, 2015.

C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna. Rethinking the inception architecture for computer vision. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 2818–2826, 2016.

C. Szegedy, S. Ioffe, V. Vanhoucke, and A. A. Alemi. Inception-v4, inception-resnet and the impact of residual connections on learning. In AAAI, 2017.

I. Tomek. Two modifications of cnn. 1976.

A. Vaswani, N. M. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin. Attention is all you need. ArXiv, abs/1706.03762, 2017.

B. Vidgen, A. Harris, D. Nguyen, R. Tromble, S. Hale, and H. Margetts. Challenges and frontiers in abusive content detection. In Proceedings of the Third Workshop on Abusive Language Online, pages 80–93, Florence, Italy, Aug. 2019. Association for Computational Linguistics. doi: 10.18653/v1/W19-3509. URL https://www.aclweb.org/anthology/W19-3509.

S. Volkova, E. Ayton, D. L. Arendt, Z. Huang, and B. Hutchinson. Explaining multimodal deceptive news prediction models, 13:659–662, Jul. 2019. URL https://ojs.aaai.org/index.php/ICWSM/article/view/3266.
F. Yang, X. Peng, G. Ghosh, R. Shilon, H. Ma, E. Moore, and G. Predovic. Exploring deep multimodal fusion of text and photo for hate speech classification. In Proceedings of the Third Workshop on Abusive Language Online, pages 11–18, Florence, Italy, Aug. 2019a. Association for Computational Linguistics. doi: 10.18653/v1/W19-3502. URL https://www.aclweb.org/anthology/W19-3502.

K.-C. Yang, O. Varol, C. Davis, E. Ferrara, A. Flammini, and F. Menczer. Arming the public with artificial intelligence to counter social bots. Human Behavior and Emerging Technologies, 1:e115, 02 2019b. doi: 10.1002/hbe2.115.

Z. Yang, Z. Dai, Y. Yang, J. Carbonell, R. Salakhutdinov, and Q. V. Le. Xlnet: Generalized autoregressive pretraining for language understanding. In NeurIPS, 2019c.

J. Zhang and I. Mani. KNN Approach to Unbalanced Data Distributions: A Case Study Involving Information Extraction. In Proceedings of the ICML'2003 Workshop on Learning from Imbalanced Datasets, 2003.

A Appendix

A.1 Sample Memes

Figure 3: Example Memes

In above figure [N] we can see few example memes from the dataset which we used in this paper. An example (a) is using the Name calling/Labeling propaganda technique by labeling the Russian vaccine with smirnoff vodka. Next example (b) applies Exaggeration technique (hyperbole the simple statement of Trump recovered from corona), there is also a Name calling technique (referring corona with ‘RONA’), and uses Glittering generalities technique. The example (c) expresses Doubt and creating a confusion in audience.