

GAME-ON: Graph Attention Network based Multimodal Fusion for Fake News Detection

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Abstract

Social media in present times has a significant and growing influence. Fake news being spread on these platforms have a disruptive and damaging impact on our lives. Furthermore, as multimedia content improves the visibility of posts more than text data, it has been observed that often multimedia is being used for creating fake content. A plethora of previous multimodal-based work has tried to address the problem of modeling heterogeneous modalities in identifying fake content. However, these works have the following limitations: (1) inefficient encoding of inter-modal relations by utilizing a simple concatenation operator on the modalities at a later stage in a model, which might result in information loss; (2) training very deep neural networks with a disproportionate number of parameters on small but complex real-life multimodal datasets result in higher chances of overfitting. To address these limitations, we propose GAME-ON, a Graph Neural Network based end-to-end trainable framework that allows granular interactions within and across different modalities to learn more robust data representations for multimodal fake news detection. We use two publicly available fake news datasets, Twitter and Weibo, for evaluations. Our model outperforms on Twitter by an average of 11% and keeps competitive performance on Weibo, within a 2.6% margin, while using 65% fewer parameters than the best comparable state-of-the-art baseline.

1 Introduction

The fast growth of social media has created a perfect environment for the diffusion of information, be it genuine or fake. However, without any quality control over the disseminated information, fake news has far-reaching consequences [Zhaoh *et al.*, 2015]. For example, the influence of fake news during the 2016 presidential election in the United States [Bovet and Makse, 2019], the dissemination of numerous myths,

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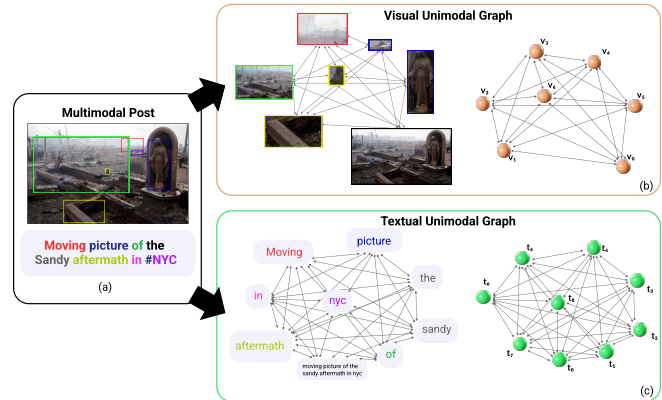


Figure 1: Overview of the graph construction pipeline for the GAME-ON framework. (a) Given a multimodal post (news sample), taken from the Twitter dataset, we extract individual fully-connected graphs for both the modalities. (b) We find objects from the image and extract their feature representations v_i . (c) For the textual graph, we first tokenize the text and extract their feature representations t_i .

and misleading information about the COVID-19 pandemic [Melki *et al.*, 2021; Sharma *et al.*, 2021]. Fake news developers, in particular, use the tactics of adding visual information to the text to craft more appealing and controversial posts to deceive users [Verstraete *et al.*, 2021]. As a result, detecting fake news while taking into account multimodal data is of utmost importance.

Recently, there has been growing interest amongst researchers in the field of multimodal fake news detection. Various deep-learning based architectures have been proposed [Khattar *et al.*, 2019; Wang *et al.*, 2018]. In addition, transfer learning strategies have become increasingly popular in identifying Fake News [Singhal *et al.*, 2019; Singhal *et al.*, 2020]. Researchers have also focused on intermodal interactions by fusing different modalities using cross-attention networks at the cost of a complex model [Wu *et al.*, 2021a; Qian *et al.*, 2021].

The shortcoming of the previous works is the inefficient fusion of different modalities using complex models. Fusing modalities using simple concatenation at a later point in the model, in particular, can result in information loss. In

addition, previous works that utilize the concatenation operator for encoding the intermodal relationship fail to explicitly address the *heterogeneity gap* [Peng and Qi, 2019], which arises in multimodal data. Even studies that have attempted to address the aforementioned issues utilized a complex model with a large number of parameters [Qian *et al.*, 2021], possibly leading to higher chances of overfitting.

The motivation behind using Graphs: Consider a multimodal post with both textual and visual content (see Figure 1). In the case of text (Figure 1 (c)), as each word is important and connected with the other in order to detect fake news, we created a textual unimodal graph. Specifically, nodes represent embeddings, which include both semantic (text as a whole) and syntactic-level (word-level) representations, while edges indicate relationships between embeddings. Thereby, representing multiple nodes for a single text (modality). There exists a connection between all the nodes in order to avoid any information loss. Similarly, in the case of image (Figure 1 (b)), it is evident that each extracted object in an image is connected with the other covering both semantic (image as a whole) and fine-grained (object-level) representation of the image. Therefore, (i) extracting both fine-grained and global representations for each modality (*nodes*) helps the model to learn complex relationships (*edges*) within and across modalities in real-world data more efficiently in a *graphical* manner, and (ii) increasing instances of interaction through direct and indirect connections between different modality nodes helps reduce the heterogeneity gap caused by inconsistencies in the distributions of distinct but semantically similar modalities.

Graph Neural Networks (GNNs) have revolutionized many fields, including network science, semantic forensics, health, visual dialogue, and have achieved excellent performance on numerous tasks. Also, in contemporary multimodal representation learning works, only a few have employed these powerful GNNs techniques [Mai *et al.*, 2020; Chen and Zhang, 2020; Han *et al.*, 2020; Sabir *et al.*, 2021; Jiang *et al.*, 2020; Arya *et al.*, 2019]. However, these works either introduce tensor factorization-based methods that are sensitive to outliers or utilize separate stages for inter- and intra-modal encoding. Therefore, unlike our proposed framework, the former introduces unwanted complexity, and the latter can not simultaneously model inter- and intra- modal relationships. Though our paper focuses on multimodal fake news detection as its application, our framework can also be generalized to other multimedia tasks.

Building on the gaps from the previous literature for multimodal fake news detection and the recent success of GNNs, the main contributions of our work are as follows:

1. We propose **GAME-ON**, a novel end-to-end trainable GNN-based framework¹ for identifying fake news on social media platforms using multimodal data;
2. The proposed framework allows for granular interactions across (inter)- and within (intra)- modalities in order to fuse them early in the framework in a two-step process, decreasing information loss;

¹Anonymized code added in the Supplementary material.

3. With fewer trainable parameters, we propose a simple approach when compared to complicated state-of-the-art models. In particular, our model has **~65%** fewer parameters than the best comparable baseline; and
4. We assess our model on two publicly available real-world datasets, MediaEval 2015 and Sina Weibo. Our model outperforms the current state-of-the-art models on Twitter by an average of **11%** in all performance indicators. On Weibo, our model maintains a competitive performance within a **2.6%** margin of the respective complex models.

The rest of the paper is organized as follows. Section 2 examines the literature broadly from multimodal perspective. The proposed framework is discussed in Section 3. The experiments using real-world datasets and the ablation study of our proposed framework are covered in Section 4. Finally, Section 5 discusses the conclusion and future directions of this work.

2 Related Work

This section covers past works that deal with multimodal approaches, which is the focus of this work.

Multimodal Fake News Detection

In the past, many approaches [Castillo *et al.*, 2011; Kwon *et al.*, 2013; Shu *et al.*, 2017; Sharma and Sharma, 2021; Butt *et al.*, 2021] have focused primarily on extracting unimodal features from the data to detect fake news. However, research has shown that inclusion of multimodal features improves model performance [Chen and Zhang, 2020]. A multimodal fake news detection system, in particular, is made up of two separate encoders for text and visual modalities. Various research have attempted to add either a novel fusion approach or a sub-task to aid in the fusion [Khattar *et al.*, 2019; Wu *et al.*, 2021a].

Various deep-learning based architectures have been used in detecting fake news on multimodal data. A Bi-Variational Autoencoder based architecture has been proposed to extract the shared representation of multimodal data, that is, learn correlations across the tweets’ text and images extracted using the Bi-LSTM network and VGG-19, respectively [Khattar *et al.*, 2019]. An event-discriminator module in the EANN architecture was introduced to remove event-specific features using adversarial style learning [Wang *et al.*, 2018]. For textual and visual features extraction, Text-CNN and VGG-19 networks were used respectively and then concatenated to find a multimodal representation. [Zhou *et al.*, 2020] focused on the relationship between the visual and textual information in a news article and introduced a new Similarity-Aware fake news detection. The feature extraction methods employed in this work were different as they first converted the image into text using a pre-trained image-to-sequence model. They then used cosine similarity to capture cross-modal similarity of two types of textual data. [Singhal *et al.*, 2019; Singhal *et al.*, 2020] leveraged pre-trained transformer-based textual encoders and VGG-19 for image feature extraction to classify fake news via transfer learning. Cross-attention networks are also heavily used in recent works that help in

improving the accuracy of the models [Ying *et al.*, 2021; Wu *et al.*, 2021b; Qi *et al.*, 2021; Wu *et al.*, 2021a].

The shortcoming of the previous mentioned works is the inefficient encoding of inter-modal relations at a later stage in a model and use of simple concatenation operator on the modalities, which could result in information loss. Specifically, this occurs as these approaches do not consider the inter-modalities relations explicitly. Moreover, existing works mentioned above lack efficient fusion of multimodal features [Wang *et al.*, 2020]. However, the authors in [Wu *et al.*, 2021a] presented a multimodal co-attention networks model in their fake news detection work, which takes care of inter modalities relations by fusing multiple modalities using co-attention maps at the cost of having a complex model. Furthermore, research [Peng and Qi, 2019] illustrates why it is necessary and challenging to bridge the heterogeneity gap caused due to inconsistent distributions and representations of various modalities. To address this issue, they employed cross-modal joint distribution of Generative Adversarial Networks to correlate different modalities.

Graph Neural Networks (GNNs) in Multimodal settings

GNNs have excelled in a multitude of disciplines, including network science, semantic forensics, health, visual dialogue [Mai *et al.*, 2020; Chen and Zhang, 2020; Han *et al.*, 2020; Sabir *et al.*, 2021; Jiang *et al.*, 2020; Arya *et al.*, 2019]. Specifically, [Jiang *et al.*, 2020] employed graph to create fine-grained cross-modal semantic links between visual and text knowledge, as well as an adaptive information selection mode to get the relevant information. [Arya *et al.*, 2019] utilized Graph Convolutional Networks to combine relational information inside and across modalities utilising a hypergraph-based data representation framework.

Inspired by their limitation of inefficient fusion of different modalities with complex models and recent success of GNNs, we propose, GAME-ON, an end-to-end trainable GNN based framework. The GAME-ON framework contains fewer number of parameters, but also takes care of the heterogeneity gap. To be particular, inter (across)-and intra (within)- modalities relationships are fused together to learn a common multimodal representations in a novel two-step process (detailed description in Section 3).

3 Methodology

The proposed framework is discussed in detail in this section.

Model Overview. The task of multimodal fake news detection can be described as a binary classification task, where the aim is to model the news (N) sample’s text(s) T and image(s) V to predict whether the given news is real or fake.² To this end, we propose an end-to-end trainable model, **GAME-ON: (Graph Attention Network-based Multimodal FusiON)** (see Figure 2). Our proposed framework consists of four stages to overcome the inherent challenges caused by heterogeneous modalities: (i) represent a

²Our model can handle multiple visual (multiple images) and text sources (headline, main content, etc.) for a given news sample. For simplification, we assume a single image and text source associated with a news sample.

news sample ($N_i = \{T_i, V_i\}$) into two fully connected graphs with nodes extracted from the text (G_T) and visual (G_V) components respectively (subsection 3.1), (ii) learn common space representations for the different modalities, and add inter-modal connections between text and visual nodes ($G_{MM} = G_T + G_V$) (subsection 3.2), (iii) utilize graph attention layer on the multimodal graph to weigh inter and intra- modal relations dynamically, to learn robust multimodal representation (subsection 3.3), and (iv) pooling and classification (subsection 3.4). In the following subsections, we introduce our framework architecture in detail.

3.1 Visual and Textual Feature Encoders

Visual Feature Encoder. To this module, we input the image V accompanying the news sample and aim to extract both global and localized representations to better capture the semantics and fine-grained structure of the image. We employ a pre-trained Faster R-CNN [Ren *et al.*, 2015] model to extract bounding boxes of objects present in the image $V = \{bb_1, bb_2, \dots, bb_l\}$, where bb_i is the i^{th} object detected by the model in image V (global representation of whole image is represented as $V = bb_0$). We then use these cropped bounding boxes and the whole image as input to a pre-trained Resnet-50 [He *et al.*, 2016] model, our vision model (VM), to extract local and global feature embeddings for the image. The output representation from the vision model \tilde{v}_i is given by:

$$\tilde{v}_i = VM(bb_i), \forall b_i \in \{bb_0, bb_1, bb_2, \dots, bb_l\} \quad (1)$$

where \tilde{v}_i is a 2048-dimensional vector. The \tilde{v}_i feature is then resized to a 768-dimensional feature vector v_i to match with the textual feature dimensions. Keeping in line with our simplistic and effective approach, we use mean pooling to achieve the required size.

For the visual modality graph $G_V = (N_V, E_V)$, the nodes N_V are represented by the extracted visual features (embeddings) from the vision model $N_V = \{v_0, v_1, v_2, \dots, v_l\}$. We assume that there exists a relationship between each visual node [Jiang *et al.*, 2020]. Therefore, the visual graph is fully connected with unweighted and bi-directional edges.

Textual Feature Encoder. To this module, we input the text accompanying the news sample, which can be viewed as a sequential list of tokens or words $T = \{w_1, w_2, \dots, w_k\}$. To capture the semantics and syntactic-level representations of the text (following the same encoding strategy as the visual encoder), we extract both context-aware token-wise representations, along with a cumulative text representation from the input text by utilizing a pre-trained Bidirectional Encoder Representations from Transformers (BERT) [Devlin *et al.*, 2018] as our language model (LM). Specifically, we employ the [CLS] and token-wise output embeddings for cumulative and token level feature embeddings, respectively. The output contextualized representation t_i from the language model is given by:

$$\{t_0, t_1, t_2, \dots, t_k\} = LM([CLS], w_1, w_2, \dots, w_k), \quad (2)$$

where t_i is a 768-dimensional feature vector, t_0 is the text-level representation.

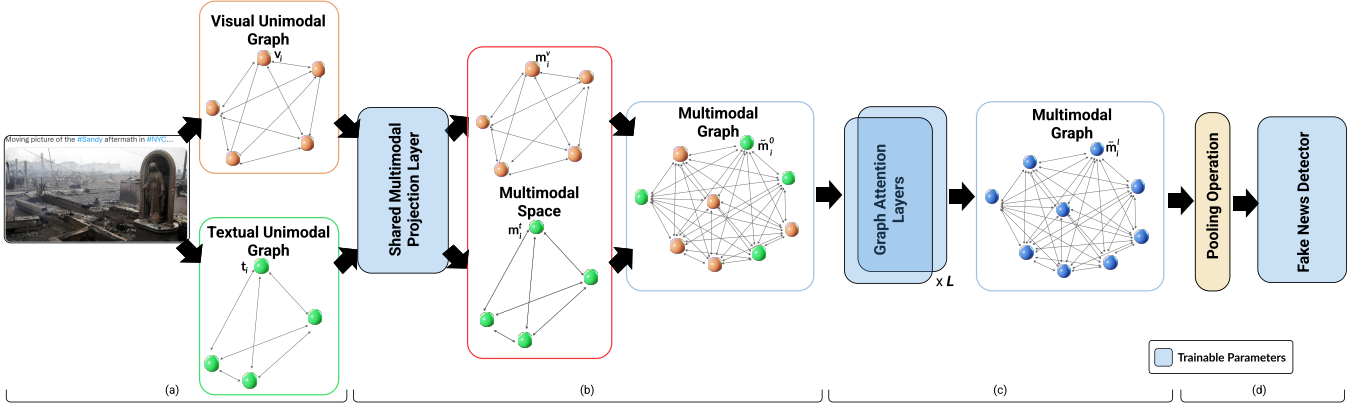


Figure 2: Overview of the GAME-ON framework. It consists of four stages. (a) Each modality is transformed into a unimodal visual and textual graph (subsection 3.1). (b) To establish common space representations of each modality, both graphs are routed into fully-connected layers and inter-modality connections are introduced (subsection 3.2). (c) The multimodal graph is given to the graph attention layer ($L=1$), which uses it to learn resilient representations (subsection 3.3). (d) The pooling and classifier are utilized to determine whether or not a news sample is fake (subsection 3.4).

For the textual modality graph $G_T = (N_T, E_T)$, the nodes are represented by the extracted textual features from the language model $N_T = \{t_0, t_t, t_2, \dots, t_k\}$. Similar to the visual graph, we assume a relationship between each textual node for consistency. Therefore, the textual graph is also fully connected with unweighted and bi-directional edges.

3.2 Shared Multimodal Space and Multimodal Graph Construction

Shared Multimodal Space. In previous multimodal representation learning and information retrieval works, researchers have discussed the need to bridge the *heterogeneity gap* that is created when dealing with different modalities and their specialized pre-trained feature encoders [Peng and Qi, 2019]. To fully capture the semantic correlation between the heterogeneous modalities, a shallow fully connected network or a weight-sharing network is employed to learn meaningful multimodal representations in a shared feature space [Peng *et al.*, 2016]. Taking inspiration from these works, we also utilize a single fully-connected feed-forward layer followed by a non-linearity, Exponential Linear Unit (ELU) to bridge the heterogeneity gap between the modalities and project the node features of textual m_j^t and visual m_i^v uni-modal graphs to common embedding space.

$$m_i^v = ELU(W_{MM}v_i + b_{MM}), \forall v_i \in \{v_0, v_1, \dots, v_k\} \quad (3)$$

$$m_j^t = ELU(W_{MM}t_j + b_{MM}), \forall t_j \in \{t_0, t_1, \dots, t_l\} \quad (4)$$

where, W_{MM} and b_{MM} are parameters for the projection layer, m_i^v and m_j^t are visual and textual feature representations.

Multimodal Graph Construction. To simultaneously model the inter- and intra-modal semantic relationship between the heterogeneous modalities, we introduce unweighted and bidirected edges between them to bridge the heterogeneity gap even further. Therefore, we connect each

text node to every image node and vice-versa. Classical concatenation or cross-attention methods can only model cross-modal relationships from a global standpoint; however, these inter-modal and intra-modal connecting edges help the model learn from dependencies arising from both within and across modalities concurrently at a more granular level. Given the individual graphs G_T and G_V , we construct a multimodal graph $G_{MM} = (N_{MM}, E_{MM})$, with the nodes $N_{MM} = \{\tilde{m}_0^0, \tilde{m}_1^0, \dots, \tilde{m}_{k+l+1}^0\} = \{m_0^v, \dots, m_k^v, m_0^t, \dots, m_l^t\}$, for simplicity we are taking \tilde{m}_i^0 as the combined notation for the textual m_j^t and visual m_i^v nodes in our multimodal graph, and $E_{MM} = \{e_{ij}\}^{(k+l+2) \times (k+l+2)}$ matrix for the fully connected multimodal graph.

3.3 Graph Attention Layer

To learn discriminative and coherent representation for each node in our multimodal graph, we employ Graph Attention Network (GAT) [Veličković *et al.*, 2017] layer. The GAT layer allows nodes to adaptively select between inter- and intra- modal connections concurrently and attend to more semantically relevant nodes in the fully connected graph. Unlike classical methods that employ separate blocks for inter- and intra- modal fusion, GAT-based layers help assign different weights to multimodal neighborhood nodes, allowing robust multimodal representation at a more granular level. The node embedding \tilde{m}^l update equation for the l^{th} layer is given by:

$$\tilde{m}^l = \sum_{j \in \mathcal{N}(i)} \alpha_{i,j} W^l \tilde{m}_j^{l-1} \quad (5)$$

where $\alpha_{i,j}$ is the attention score between node i and node j :

$$\alpha_{i,j}^l = \text{softmax}_i(e_{i,j}^l) \quad (6)$$

$$e_{i,j}^l = \text{LeakyReLU}(\bar{a}^T [W \tilde{m}_i \| W \tilde{m}_j]) \quad (7)$$

where $\|$ is the concatenation operation, LeakyReLU stands for Leaky Rectified Linear Unit.

	Twitter	Weibo
# of Real News	5,870	3,642
# of Fake News	8,023	4,211
# of Images	410	7,853

Table 1: Statistics of two real-world datasets.

3.4 Fake News Detector

Pooling Operator. Following our efficient and straightforward architectural choices, we use global mean node pooling for selecting a graph-level representation for our multimodal news-level graph h_{GMM} .

$$h_{GMM} = \text{pool}(\{\tilde{m}_0^l, \tilde{m}_1^l, \dots, \tilde{m}_{k+l+1}^l\}) \quad (8)$$

Classification. To this module, we input the learned multimodal graph-level representation and aim to classify the news sample as fake or real. We employ a shallow two-layer fully connected feed-forward network with intermediate ReLU non-linearity and output dimension to match with target space of two classes followed by a softmax function to convert logits into class probabilities. Let $\hat{P}_n = [\hat{P}_n^0, \hat{P}_n^1]$ be the output predicted vector and Y_n be the ground-truth label for the n^{th} news sample, where \hat{P}_n^0 and \hat{P}_n^1 are the predicted probability of the n^{th} sample being real and fake, respectively. We minimize the cross-entropy loss to train the model end-to-end for fake news detection:

$$L(\theta) = \frac{1}{N} \sum_{i=1}^N Y_i \log \hat{P}_i^0 + (1 - Y_i) \log(1 - \hat{P}_i^1) \quad (9)$$

where N is the number of news samples.

4 Experiments and Results

4.1 Datasets

We evaluate the efficacy of our proposed GAME-ON framework on two widely adopted social media multimodal fake news datasets: (i) MediaEval (Twitter) [Boididou *et al.*, 2015] and (ii) Weibo [Jin *et al.*, 2017]. Table 1 shows the statistics of the two datasets.

The **Twitter dataset** was released for the Verifying Multimedia Use Task as a part of MediaEval. It consists of two parts: the development and the test set. For fair evaluation with other baselines, we use development set for training and the test set for the evaluation.

The **Weibo dataset** was collected from a Chinese microblogging website, Sina Weibo [Jin *et al.*, 2017]. We used the publicly available version of this dataset used by authors of [Wang *et al.*, 2018].

4.2 Implementation Details

We implemented our proposed graphical multimodal fusion approach via Deep Graph Library³ and PyTorch⁴ framework. For all the experiments, we use GeForce GTX 1080 Ti GPU

³<https://github.com/dmlc/dgl>

⁴<https://github.com/pytorch/pytorch>

with 11 GB memory. We use the pre-trained ‘bert-base-uncased’ and ‘bert-base-chinese’ BERT models from HuggingFace⁵ and pre-trained CNN model from torchvision⁶ for textual and visual node feature extraction, respectively. The common embedding space dimension to which we project the text and image features is 768. For the GAT layer (output dimension: 256), we employ ELU non-linearity, 0.4 feature dropout rate, and one attention head. For the fake news detector, we use an intermediate feature dimension of 128 and a dropout rate of 0.4. We used an effective batch size of 512 and trained the model end-to-end with Adam optimizer [Kingma and Ba, 2014], with an initial learning rate of 1e-4 with a linearly decreasing scheduler.

4.3 Multimodal Baselines

We compare multimodal approaches to assess the performance of our proposed approach, GAME-ON.

EANN [Wang *et al.*, 2018] extracts textual and visual data separately using pre-trained models and combines them to feed into a fake news detector and event discriminator to eliminate any event-specific features.

MVAE [Khattar *et al.*, 2019] uses bimodal variational autoencoder and a fake news classifier, this model provided a shared representation of multimodal data.

CALM [Wu *et al.*, 2021b] employs a cross-modal fusion network with orthogonal latent memory, the CALM framework is utilized to identify rumors.

HMCAN [Qian *et al.*, 2021] uses a hierarchical attention model that considers both the text’s hierarchical semantics and multimodal contextual data.

SpotFake [Singhal *et al.*, 2019] utilizes both the textual and visual aspects of an article by simple concatenation.

MFN [Chen *et al.*, 2021] gives appropriate weights to the complementary modalities, the self-attentive fusion approach is used to perform feature-level fusion.

MCAN [Wu *et al.*, 2021a] uses various co-attention layers are used to learn inter-modality relations, with visual features being fused first, followed by textual features.

4.4 Results

Table 2 demonstrates the experimental results of our proposed model GAME-ON on the two datasets and the baselines.

We observe that the proposed GAME-ON model surpasses the current state-of-the-art model CALM on the Twitter dataset by an average of **11%** margin in all the performance metrics. On the Weibo dataset, GAME-ON achieves competitive performance within a 2.6% margin of the respective complex and large state-of-the-art models, while having significantly less number of trainable parameters.⁷

We also compare our proposed framework with the comparable baselines on the axis of the model’s size or the number of trainable parameters (Table 3). Our model contains the least number of trainable parameters when compared to

⁵<https://github.com/huggingface/transformers>

⁶<https://pytorch.org/vision/stable/models.html>

⁷To compare with the most recent and state-of-the-art papers, we use HMCAN and MCAN just for the Weibo dataset, as done so in the original papers.

Dataset	Method	Acc	Prec	Recall	F1
Twitter	EANN	0.715	0.822	0.638	0.719
	MVAE	0.805	0.869	0.588	0.702
	SpotFake	0.778	0.751	0.900	0.82
	MFN	0.806	0.799	0.777	0.785
	CALM	0.845	0.785	0.831	0.807
	GAME-ON	0.958	0.944	0.905	0.924
Weibo	EANN	0.827	0.847	0.812	0.829
	MVAE	0.824	0.854	0.769	0.809
	MFN	0.808	0.806	0.806	0.807
	CALM	0.846	0.843	0.864	0.853
	HMCAN	0.885	0.920	0.845	0.881
	MCAN	0.899	0.913	0.889	0.901
	<i>GAME-ON</i>	<i>0.874</i>	<i>0.878</i>	<i>0.873</i>	<i>0.875</i>

Table 2: Performance comparison of GAME-ON framework with state-of-the-art baselines on Twitter and Weibo datasets. *Acc*, *Prec*, and *F1* represent Accuracy, Precision, and F1-score, respectively.

Model Name	# of Trainable Parameters
SpotFake	~ 11 million +
HMCAN	~ 20 million +
MCAN	~ 2.9 million +
GAME-ON	1,017,730 (~ 1 million)

Table 3: Comparison of GAME-ON framework with comparable baselines based on model size (number of trainable parameters). GAME-ON utilizes 65% fewer trainable parameters than MCAN.

other state-of-the-art models with comparable performance. The closest baseline model, MCAN has roughly 2.9 million trainable parameters, whereas our model contains around 1 million trainable parameters, that is ~65% less than the best comparable baseline.⁸

4.5 Ablation Study

To study the importance of our fusion framework, we conduct an ablation study and the results are summarized in Table 4. We compare our GAME-ON model with unimodal graphical

Dataset	Type	Method	Acc	F1
Twitter	Unimodal	Textual	0.558	0.508
		Visual	0.862	0.677
	Multimodal	Concatenation	0.897	0.782
		GCN-Fusion	0.929	0.900
		GAME-ON	0.958	0.924
Weibo	Unimodal	Textual	0.820	0.822
		Visual	0.537	0.556
	Multimodal	Concatenation	0.840	0.841
		GCN-Fusion	0.846	0.850
		GAME-ON	0.874	0.875

Table 4: Performance comparison of GAME-ON framework with its variants on Twitter and Weibo datasets. *Acc*, and *F1* represent Accuracy, and F1-score, respectively.

⁸We also tried to calculate the CALM model’s parameters. However, due to insufficient parameter values provided in the paper, we are unable to retrieve their total trainable parameters.

approaches (Textual and Visual in Table 4) to demonstrate the importance of our multimodal framework. We also compare our framework with two other multimodal graphical methods to evaluate the efficacy of (a) graph attention layers to attend to relevant nodes in the fully connected graph adaptively and (b) multimodal connections for granular inter-modal interaction. To this end, we create two separate versions of our model.

1. **GCN-Fusion:** we replace our GAT layer with simple graph convolution (GCN) layer to highlight (a). GAME-ON model outperforms this model on both datasets by an average of **2.1%** and **2.7%** in F1-score and accuracy, respectively.
2. **Concatenation:** we remove the inter-modal connections and feed textual and visual graphs to GAT layer individually, followed by mean pooling and concatenating the visual and textual graphical representations to emphasize on (b). Results in Table 4 indicate that introducing inter-modal edges and allowing the model to learn both intra- and intermodal dependencies simultaneously decreases the heterogeneity gap and improves the performance on both datasets by an average of **5.7%** and **4.6%** in F1-score and accuracy, respectively.

5 Conclusions

In this work, we proposed GAME-ON, an end-to-end trainable GNN based framework for detecting fake news. We evaluated our framework’s efficacy on two publicly available multimodal datasets. Our work overcomes two significant shortcomings of previous works. First, works that encode the inter-modal relation using the concatenation operator fail to clearly address the heterogeneity gap that occurs in multimodal data. Second, even research that sought to address the first problem used complicated models to combine the various modalities, implying a higher risk of overfitting. Using a two-step procedure, the framework enables for granular interactions within and across distinct modalities to merge them early in the framework. Our model outperforms the current state-of-the-art models on the Twitter dataset by an average of **11%** in all performance indicators when compared to complex state-of-the-art models. On Weibo, our model maintains a competitive performance within a **2.6%** margin of the respective complex state-of-the-art models. In addition, we compared our model with state-of-the-art models in terms of trainable parameters. According to our findings, our model has ~65% fewer parameters than the best comparable baseline. For future work, our work can be extended to include datasets with long articles. Full-length articles when transformed to textual unimodal graphs using word-level representation, can result in big graphs (utilizing huge memory space). In such a scenario, using sentence embeddings rather than word embeddings might be a feasible alternative.

References

- [Arya *et al.*, 2019] Devanshu Arya, Stevan Rudinac, and Marcel Worring. Hyperlearn: a distributed approach for representation learning in datasets with many modalities. In *ACM MM*, pages 2245–2253, 2019.

- [Boididou *et al.*, 2015] Christina Boididou, Katerina Andreadou, Symeon Papadopoulos, Duc-Tien Dang-Nguyen, Giulia Boato, Michael Riegler, Yiannis Kompatsiaris, et al. Verifying multimedia use at mediaeval 2015. *MediaEval*, 3(3):7, 2015.
- [Bovet and Makse, 2019] Alexandre Bovet and Hernán A Makse. Influence of fake news in twitter during the 2016 us presidential election. *Nature communications*, 10(1):1–14, 2019.
- [Butt *et al.*, 2021] Sabur Butt, Shakshi Sharma, Rajesh Sharma, Grigori Sidorov, and Alexander Gelbukh. What goes on inside rumour and non-rumour tweets and their reactions: A psycholinguistic analyses. *arXiv preprint arXiv:2112.03003*, 2021.
- [Castillo *et al.*, 2011] Carlos Castillo, Marcelo Mendoza, and Barbara Poblete. Information credibility on twitter. In *WWW*, pages 675–684, 2011.
- [Chen and Zhang, 2020] Jiayi Chen and Aidong Zhang. Hgmf: Heterogeneous graph-based fusion for multimodal data with incompleteness. In *ACM SIGKDD*, pages 1295–1305, 2020.
- [Chen *et al.*, 2021] Jiaxin Chen, Zekai Wu, Zhenguo Yang, Haoran Xie, Fu Lee Wang, and Wenyin Liu. Multimodal fusion network with latent topic memory for rumor detection. In *IEEE ICME*, pages 1–6. IEEE, 2021.
- [Devlin *et al.*, 2018] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018.
- [Han *et al.*, 2020] Yi Han, Shanika Karunasekera, and Christopher Leckie. Graph neural networks with continual learning for fake news detection from social media. *arXiv preprint arXiv:2007.03316*, 2020.
- [He *et al.*, 2016] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *IEEE CVPR*, pages 770–778, 2016.
- [Jiang *et al.*, 2020] Xiaoze Jiang, Siyi Du, Zengchang Qin, Yajing Sun, and Jing Yu. Kbn: Knowledge-bridge graph network for adaptive vision-text reasoning in visual dialogue. In *ACM MM*, pages 1265–1273, 2020.
- [Jin *et al.*, 2017] Zhiwei Jin, Juan Cao, Han Guo, Yongdong Zhang, and Jiebo Luo. Multimodal fusion with recurrent neural networks for rumor detection on microblogs. In *ACM MM*, pages 795–816, 2017.
- [Khattar *et al.*, 2019] Dhruv Khattar, Jaipal Singh Goud, Manish Gupta, and Vasudeva Varma. Mvae: Multimodal variational autoencoder for fake news detection. In *WWW*, pages 2915–2921, 2019.
- [Kingma and Ba, 2014] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.
- [Kwon *et al.*, 2013] Sejeong Kwon, Meeyoung Cha, Kyomin Jung, Wei Chen, and Yajun Wang. Prominent features of rumor propagation in online social media. In *IEEE ICDM*, pages 1103–1108. IEEE, 2013.
- [Mai *et al.*, 2020] Sijie Mai, Songlong Xing, Jiakuan He, Ying Zeng, and Haifeng Hu. Analyzing unaligned multimodal sequence via graph convolution and graph pooling fusion. *arXiv preprint arXiv:2011.13572*, 2020.
- [Melki *et al.*, 2021] Jad Melki, Hani Tamim, Dima Hadid, Maha Makki, Jana El Amine, and Eveline Hitti. Mitigating infodemics: The relationship between news exposure and trust and belief in covid-19 fake news and social media spreading. *Plos one*, 16(6):e0252830, 2021.
- [Peng and Qi, 2019] Yuxin Peng and Jinwei Qi. Cm-gans: Cross-modal generative adversarial networks for common representation learning. *ACM TOMM*, 15(1):1–24, 2019.
- [Peng *et al.*, 2016] Yuxin Peng, Xin Huang, and Jinwei Qi. Cross-media shared representation by hierarchical learning with multiple deep networks. In *IJCAI*, pages 3846–3853, 2016.
- [Qi *et al.*, 2021] Peng Qi, Juan Cao, Xirong Li, Huan Liu, Qiang Sheng, Xiaoyue Mi, Qin He, Yongbiao Lv, Chenyang Guo, and Yingchao Yu. Improving fake news detection by using an entity-enhanced framework to fuse diverse multimodal clues. In *ACM MM*, pages 1212–1220, 2021.
- [Qian *et al.*, 2021] Shengsheng Qian, Jinguang Wang, Jun Hu, Quan Fang, and Changsheng Xu. Hierarchical multi-modal contextual attention network for fake news detection. In *ACM SIGIR*, pages 153–162, 2021.
- [Ren *et al.*, 2015] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. *NeurIPS*, 28:91–99, 2015.
- [Sabir *et al.*, 2021] Ekraam Sabir, Ayush Jaiswal, Wael AbdAlmageed, and Prem Natarajan. Meg: Multi-evidence gnn for multimodal semantic forensics. In *ICPR*, pages 9804–9811, 2021.
- [Sharma and Sharma, 2021] Shakshi Sharma and Rajesh Sharma. Identifying possible rumor spreaders on twitter: A weak supervised learning approach. In *2021 International Joint Conference on Neural Networks (IJCNN)*, pages 1–8. IEEE, 2021.
- [Sharma *et al.*, 2021] Shakshi Sharma, Rajesh Sharma, and Anwitaman Datta. Misleading the covid-19 vaccination discourse on twitter: An exploratory study of infodemic around the pandemic. *arXiv preprint arXiv:2108.10735*, 2021.
- [Shu *et al.*, 2017] Kai Shu, Amy Sliva, Suhang Wang, Jiliang Tang, and Huan Liu. Fake news detection on social media: A data mining perspective. *ACM SIGKDD explorations newsletter*, 19(1):22–36, 2017.
- [Singhal *et al.*, 2019] Shivangi Singhal, Rajiv Ratn Shah, Tanmoy Chakraborty, Ponnurangam Kumaraguru, and Shin’ichi Satoh. Spofake: A multi-modal framework for fake news detection. In *IEEE BigMM*, pages 39–47. IEEE, 2019.
- [Singhal *et al.*, 2020] Shivangi Singhal, Anubha Kabra, Mohit Sharma, Rajiv Ratn Shah, Tanmoy Chakraborty, and Ponnurangam Kumaraguru. Spofake+: A multimodal framework for fake news detection via transfer learning (student abstract). In *AAAI*, pages 13915–13916, 2020.
- [Veličković *et al.*, 2017] Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Yoshua Bengio. Graph attention networks. *arXiv preprint arXiv:1710.10903*, 2017.
- [Verstraete *et al.*, 2021] Mark Verstraete, Derek E Bambauer, and Jane R Bambauer. Identifying and countering fake news. *Hastings Law Journal*, 73, 2021.
- [Wang *et al.*, 2018] Yaqing Wang, Fenglong Ma, Zhiwei Jin, Ye Yuan, Guangxu Xun, Kishlay Jha, Lu Su, and Jing Gao. Eann: Event adversarial neural networks for multi-modal fake news detection. In *ACM SIGKDD*, pages 849–857, 2018.
- [Wang *et al.*, 2020] Youze Wang, Shengsheng Qian, Jun Hu, Quan Fang, and Changsheng Xu. Fake news detection via knowledge-driven multimodal graph convolutional networks. In *ICMR*, pages 540–547, 2020.

- [Wu *et al.*, 2021a] Yang Wu, Pengwei Zhan, Yunjian Zhang, Liming Wang, and Zhen Xu. Multimodal fusion with co-attention networks for fake news detection. In *ACL-IJCNLP*, pages 2560–2569, 2021.
- [Wu *et al.*, 2021b] Zekai Wu, Jiabin Chen, Zhenguo Yang, Haoran Xie, Fu Lee Wang, and Wenyin Liu. Cross-modal attention network with orthogonal latent memory for rumor detection. In *WISE*, pages 527–541. Springer, 2021.
- [Ying *et al.*, 2021] Long Ying, Hui Yu, Jinguang Wang, Yongze Ji, and Shengsheng Qian. Multi-level multi-modal cross-attention network for fake news detection. *IEEE Access*, 9:132363–132373, 2021.
- [Zhao *et al.*, 2015] Zhe Zhao, Paul Resnick, and Qiaozhu Mei. Enquiring minds: Early detection of rumors in social media from enquiry posts. In *WWW*, pages 1395–1405, 2015.
- [Zhou *et al.*, 2020] Xinyi Zhou, Jindi Wu, and Reza Zafarani. Safe: Similarity-aware multi-modal fake news detection. *arXiv preprint arXiv:2003.04981*, 2020.