




## Attention-Enhanced Hypergraph Neural Network for Fake News Detection in Online Social Networks

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### Abstract:

The speed of information transmission in online social networks today makes fake news a new challenge for public trust, social stability, and information credibility. The majority of classic fake news detection models are text-based in articles that do not make use of the well-refined flow structures that take place when users direct their interaction on a state space of social media, and which would responsabilize propagation patterns embedded in this user-directed interaction. In order to fill this gap, we propose our Attention-Enhanced Hypergraph Neural Network (AE-HGNN) model for fake news identification. The proposed framework, in turn, formulates a hypergraph to jointly capture high-order relationships of news articles and users with the injection of social interactions and propagation. Additionally, there is an inbuilt attention mechanism to enhance contributor users and informative connections. This enables us to propose a model incorporating textual semantic representations of the news content and user credibility features in order to improve our understanding of misinformation proliferation. We ran thorough experiments for the proposed method, on benchmark datasets such as PolitiFact and Gossip Cop to assess the prediction effective of Method. The experimental results demonstrate that the proposed AE-HGNN framework is able to substantially outperform a series of state-of-the-art fake news detection models and can achieve up to 98% accuracy. Results further show that the combination of hypergraph learning and attention mechanism is effective to model complex user-news interactions, and therefore significantly improve the performance of fake news detection during online social networks.

**Keywords:** Fake News Detection; Hypergraph Neural Networks; Social Network Analysis; Attention Mechanism; User Credibility Modeling.

### 1-Introduction

In the last two decades with rise of online social networks, information creation, sharing and consumption has changed drastically. Twitter, Facebook, and other social media services enable users to rapidly share news and views with a worldwide audience. While this accessibility is a positive attribute, the same frameworks that distributed it

equally facilitated the quick dissemination of falsehood and phony news — an emerging threat in recent decades [1]–[3]. Fake news is the deliberate preparation of false or misleading information passed off as genuine news, usually in an attempt to manipulate public opinion, create social panic, or alter political outcomes [4].

What fake news had a plethora of roots and, at the same time, touched many fields. In the political domain, we know that misinformation campaigns influence elections and set conversations [5]. Such a collapse of the structure of regular message construction is especially marked in events around health care, where false news and mis/disinformation, particularly related to treatment modalities or approaches to prevent them, run rampant, prompting (smug)confusion on worldwide threats such as COVID-19 [6], [7]. This points to how desperately we need effective automated fake news detection systems that can filter such media out of moneyed spaces online.

The early approaches of the fake news detection research focused on content-oriented models where features from articles were extracted and investigated. Machine learning and deep learning models, including CNNs, RNNs, and transformer-based models (i.e., BERT), have been applied to identify linguistic patterns of dissemination of misinformation [8], [9]. Early detection techniques, although with some good performance (and even though they are stand-alone and do not consider the social context of news propagation), are mostly not sufficient in modeling complex scenarios for misinformation [10].

It has been demonstrated in recent works that the social context information (e.g., user engagement, propagation feature) is indeed important and helps improve fake news detection significantly [11]. Social networks are relational, as these types of platforms let many users interact, share, and comment on news articles. In a social world where users participate in the process of information propagation, one of the key challenges is how to transmit knowledge. Knowing how these interactions are modelled means that you get a signal regarding the legitimacy of your information and the behavior of users who would share such information. This leads to GNNs, which are attracting significant interest due to their ability to build knowledge about the structural relations between users and news content [12], making graph-based deep learning models an appropriate choice in this context.

However, typical graph-based methods fail to capture the complex relationships among various entities, leading to a limitation in their representation capabilities. Around the world, many heterogeneous stories involve multiple users who interact with or share these different elements. Graph-structured data usually describes pairwise relations and does not model these sophisticated interactions completely. To tackle this scenario, hypergraph neural networks have recently been proposed as an efficient framework for modeling high-order interactions between multiple nodes in a network [13], [14]. Hypergraph learning can better model the interaction of users and news as hyperedges connecting multiple nodes, to capture the collective dynamics of information flowing in a social network.



**Figure 1. Example of Fake News Dissemination in Online Social Media [15]**

Inspired by these observations, we propose a fake news detection method based on an Attention-Enhanced Hypergraph Neural Network (AE-HGNN). We have proposed a framework that combines textual semantic representations with user credibility modeling in an equilibrated hypergraph learning architecture. In addition,

through the attention mechanism to find out the weak users and extract valuable links in the propagation network. Through this design, the proposed model can effectively capture the content features and social interaction patterns, eventually improving the accuracy and robustness of fake news detection. An example of fake news dissemination via interaction of users in social networks is depicted in Figure 1.

## Contributions

The main contributions of this work are summarized as follows:

- A novel **Attention-Enhanced Hypergraph Neural Network (AE-HGNN)** is proposed to capture complex high-order relationships between users and news articles in social networks.
- A **user credibility modeling module** is introduced to incorporate behavioral patterns associated with fake news dissemination and to improve representation learning in the propagation network.
- A **feature fusion mechanism** is developed to integrate semantic news representations with user credibility embeddings, enabling the model to effectively combine textual and social contextual information.
- Extensive experiments conducted on benchmark datasets demonstrate that the proposed framework achieves **up to 98% detection accuracy**, outperforming several state-of-the-art fake news detection models.

## 2- Related Work

The detection of fake news has become a hot topic in recent years, with the emergence and rapid expansion of social media platforms as well as a more mobile society where news spreads much faster. There are many methods used by researchers to detect fake news automatically based on different factors, including textual features, user activity, and propagation structure in the online social networks. Previous works can normally be divided into three categories: content-based fake news detection, social context-based detection, and hypergraph-based learning methods.

### 2.1 Content-Based Fake News Detection

Initial research works in fake news detection were mainly based on just textual content analysis of news articles using various varieties of machine learning and deep learning approaches. Feature engineering, where features like lexical patterns, sentiment analysis, and writing styles were manually crafted to differentiate between fake and legitimate news articles [16][17].

Due to the rapid evolution of deep learning, many neural network models have been adopted due to their capability of automatically extracting discriminative features from text data. Convolutional Neural Networks (CNNs) are increasingly adopted for recognizing local semantic statistics in news content and show good performance in fake content detection [18][19]. Similarly, Recurrent Neural Networks (RNNs) alongside their extensions such as Long Short-Term Memory (LSTM) networks have been employed to model sequential dependencies within textual data and learn relevant context in the articles [20][21].

In recent years, transformer-based language models, e.g., BERT, have also been remarkably successful in information retrieval and even fake news detection [22]. These models utilize large-scale pretraining and contextualized word embeddings to enhance the semantic grasp of textual data. Content-based SMS, despite its effectiveness, often relies only on textual features and may miss informative signals from user engagements and information dissemination in social networks.

### 2.2 Social Context-Based Fake News Detection

To overcome the drawback due to the contents-based method, recent researches are investigating social context information with fake news detection frameworks. Social context is the link between users and news content in online platforms, involving user engagement patterns [23], sharing behavior, and propagation structures.

User-related properties include the number of followers, user credibility scores, and interaction frequency, are known to be valuable indicators for misinformation spreading [24]. Moreover, constructing the propagation structure of news content has helped detect suspicious information dissemination patterns. Fake news often travels in ways

that are different than those of genuine news, and exhibits unique propagation characteristics on social networks [25].

Graph-based deep learning models are broadly employed to capture structural relations in social networks. Graph Convolution Networks (GCN) [26] and Graph Attention Networks (GATs) [27] have performed well in inferring user–news interactions, as they work by learning representations from the network structures. Particularly, these models take users and news articles as the nodes of a graph, and then learn such relational patterns from users to items through some kinds of message-passing mechanisms. However, conventional graph representations have the limitation of representing relationships between pairs, which does not characterize the complex relation among a large number of actors engaged in news propagation.

### 2.3 Hypergraph Learning for Social Network Analysis

Considering the shortcomings of all graph models, one limitation being that it is only able to express 2D relationships, researchers have been actively considering and evaluating hypergraph neural networks for modelling high-order relationships in complex networks [28]. While classical graphs are generally limited in that an edge can only connect two nodes, hypergraphs enable a single hyperedge to intersect with several nodes at once, making them ideal candidates for modelling group interactions and collective behaviours within social networks [29].

Hypergraph decomposition techniques are effective in a variety of areas, such as collaborative filtering recommendation systems, biological networks, and social networks. Hypergraph neural networks can represent the collective dynamics of information dissemination more effectively by representing higher-order interactions among multiple users and news articles [30].

Applying hypergraph learning in misinformation detection tasks has just begun recently, achieving better performance than traditional graph-based methods. Such methods utilize hypergraph convolution and attention mechanisms to capture complex relations between users and news items, thereby improving representation learning for fake news detection [31]. Inspired by these advances, in this study, we propose an AE-HGNN designed to enrich hypergraph learning with textual semantic features and user credibility modeling.

## 3- Preliminaries

In this section, we introduce the basic helpful concepts and formal definitions that will be used for proposing the fake news detection framework. Specifically, it describes the notation system, hypergraph representation to model social interactions and formal formulation of fake news detection problem.

### 3.1 Notations

Let  $N = \{n_1, n_2, \dots, n_t\}$  denote the set of news articles, where *represents* the total number of news instances in the dataset. Each news article  $n_i$  contains textual information and is associated with a set of users who interact with or share the content on social media platforms. Let  $U = \{u_1, u_2, \dots, u_m\}$  denote the set of users participating in news dissemination within the social network, where *m represents* the total number of users. Each user  $u_j$  may interact with one or more news articles through activities such as posting, sharing, commenting, or reacting. To extract representation, we can connect each user with a feature vector that describes their behavior. Examples of these include number of followers, number of followings, verification status, and activity frequency. News articles are transformed into semantic embeddings obtained through pretrained language models on the text itself.

### 3.2 Hypergraph Definition

This work takes a hypergraph to model the complicated interaction between multiple users and news articles. While classical graphs can only describe a pairwise connection between two nodes, a hypergraph allows one edge to connect several nodes at once. This feature makes hypergraphs especially appropriate for modeling social media environments in which several users might reference a single news article at once. Figure 2 illustrates the difference

between classical graphs and hypergraphs, where the traditional graph represents pairwise connections, but a hyperedge of a hypergraph can connect multiple nodes.

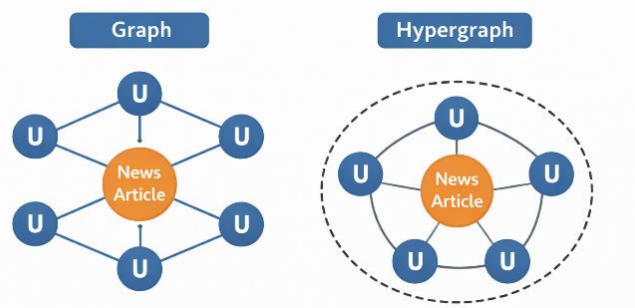
Formally, a hypergraph is defined as:

$$G = (V, E, X) \quad (1)$$

where

- $V$  represents the set of nodes in the network. In the proposed framework, nodes correspond to users participating in news propagation.
- $E$  represents the set of hyperedges, where each hyperedge corresponds to a news article connecting multiple users who interact with or share that news item.
- $X$  represents the node feature matrix, where each row corresponds to the feature representation of a user in the network.

Through this representation, a hyperedge can capture the collective interaction of multiple users with the same news article, enabling the model to learn high-order relational patterns in social networks.



**Figure 2. Comparison between graph and hypergraph representations**

### 3.3 Problem Formulation

The objective of fake news detection is to determine whether a given news article is fake or real. Within the hypergraph framework, this problem is formulated as a hyperedge classification task. Given a hypergraph  $G = (V, E, X)$ , each hyperedge  $e_i \in E$  represents a news article associated with a group of users who interacted with the content. The goal is to learn a classification function:

$$f: E \rightarrow \{0,1\} \quad (2)$$

where

- 0 indicates **real news**, and
- 1 indicates **fake news**.

By leveraging both textual information and social interaction patterns, the model learns discriminative representations that enable accurate classification of news articles within the hypergraph structure.

## 4- Proposed Method

In this section, we introduce the Attention-Enhanced Hypergraph Neural Network (AE-HGNN) framework that is proposed to detect fake news in online social networks effectively. We propose a model that combines textual semantic features obtained by vectorizing news payload with social aspects of user interactions. Specifically, via hypergraph neural networks, the framework can model complex high-order relationships of users who have spread news articles. Furthermore, an attention mechanism is integrated into the propagation model to highlight users with more influence and interactions that contain a wealth of information about fake news, making the representation learning of fake news detection better.

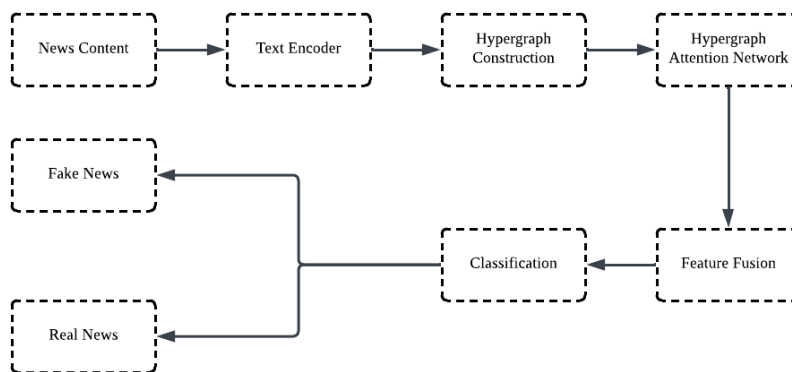
#### 4.1 Framework Overview

In Section 4, we center and present the high-level architecture of AE-HGNN, which incorporates and unifies content-based features and social contextual information into a single learning framework. The semantic representation is first extracted from news articles by the text encoding module. These encodings summarize the linguistic structures and contextual meanings discovered in the news articles.

Then, we use user–news interactions extracted from social media platforms to build a hypergraph structure in which each news article represents a hyperedge that connects multiple users who interacted with or shared the news front. This enables the model to learn complex correlations among users participating in the spread of news articles.

From this hypergraph, we can use an HGAT to learn high-order relational patterns of users. An attention mechanism allows the model to assign different weight values to users based on their influence and credibility in the propagation network. XGAT is used to learn the representations, which are then fused by a feature fusion module that binds textual semantic embeddings with user credibility features. At last, the fused feature representation is given to a classification layer which predicts if the given news article is fake or real.

Figure 3 shows the high-level design of our proposed framework, visually outlining the workflow and interactions within its model.



**Figure 3. Overall architecture of the proposed AE-HGNN framework**

#### 4.2 News Semantic Encoder

The Semantic-Enhanced news recommendation framework utilizes a pre-trained language model to extract textual contextual representations from articles, assisting the network in building semantic information. Consequently, models like Bidirectional Encoder Representations from Transformers (BERT) are leveraged in this study as they excel in capturing contextual dependencies and semantic relationships within the textual data.

Given a news article  $n_i$ , the semantic encoder transforms the textual content into a dense vector representation that captures meaningful linguistic features. Formally, the semantic representation of a news article can be defined as:

$$z_e = M(n_i) \quad (3)$$

where  $M(\cdot)$  denotes the semantic encoder, which maps the textual input into a high-dimensional embedding vector  $z_e$ . These embeddings serve as the primary textual features used in the subsequent stages of the proposed framework.

#### 4.3 User Credibility Modeling

User behavior data is similarly relevant in the context of textual elements: user behavior during both when planting misinformation and after exposure to it. Some examples could be sharing behaviour and interaction in

targeted, specific user groups. The proposed framework can also model user credibility, allowing one to study the associated content behaviors when news spreads.

Features are derived from profiles and activities of users on the social media website. These can be characteristics of the user, such as a user's authority, user trustworthiness, and user's activity within the network. Concretely, the proposal model takes a number of user features into account: The follower and friend (followings) count, if an account is verified, and how active they are on posts. These characteristics serve as valuable indicators for differentiating between credible users and possibly dubious accounts participating in misinformation dissemination. User-specific attributes that were used to model user credibility in the proposed framework are also summarized in Table 1, along with their detailed description.

**Table 1. User attribute features used for credibility modeling**

Feature	Description
Followers	Number of followers
Friends	Number of followers
Verified	User verification status
Activity	Posting frequency

#### 4.4 Hypergraph Neural Network

The proposed framework utilizes a hypergraph neural network, which allows us to model the complex connections of user co-interaction on the same news article. Compared to traditional graphs, which only create pairwise interactions, hypergraphs can establish a single hyperedge that connects multiple nodes at once, leading us to model high-order user-group privacy interaction in the network.

We utilize hypergraph convolution to propagate information through the connections in the hypergraph and learn meaningful representations of its nodes. The hypergraph convolution operation is formulated as [32]:

$$Z^{(l)} = \sigma \left( D_v^{-1/2} H W D_e^{-1} H^T D_v^{-1/2} Z^{(l-1)} \right) \quad (4)$$

where

- $Z^{(l)}$  represents the node embeddings at layer  $l$
- $H$  denotes the incidence matrix representing the hypergraph structure
- $W$  represents the learnable weight matrix
- $D_v$  and  $D_e$  denote the degree matrices of nodes and hyperedges, respectively
- $\sigma(\cdot)$  represents a nonlinear activation function

Through this process, the model captures high-order relational patterns among users participating in the dissemination of news articles.

#### 4.5 Feature Fusion Module

The proposed framework performs feature fusion by integrating both textual semantic embeddings and user credibility representations after extraction. Module 8: Integrating semantic and structural information from news content and user interactions.

The fusion process is performed using a concatenation operation, which combines the news representation and user credibility embedding into a single feature vector as follows:

$$f_i = \text{Concat}(z_i, u_i) \quad (5)$$

This fused representation captures both content-level semantics and social context features, allowing the model to generate more informative embeddings for fake news detection.

#### 4.6 Fake News Classification

This architecture consists of three modules: A semantic encoder that captures relevant features, a user credibility modeling module that assigns an authenticity score based on the user, and a final layer performing fake news classification upon any of those two fused feature representations. This feature vector is passed to an MLP classifier to predict the class distribution. The classifier learns from both the content-level features and social context features, patterns that help in identifying the two news types [26].

Lastly, as the last layer of the model, we applied a SoftMax activation function, which predicted the probability distribution for classes. We can mathematically formulate the prediction function as:

$$y = \text{softmax}(Wf + b) \quad (6)$$

where  $f$  represents the fused feature vector obtained from the feature fusion module, while  $W$  and  $b$  denote the learnable parameters of the classification layer. The model is trained using a cross-entropy loss function to minimize the difference between predicted and true labels.

The complete training process of the proposed AE-HGNN framework is summarized in Algorithm 1, which describes the major steps involved in feature extraction, hypergraph construction, representation learning, and final classification.

#### Algorithm 1. Training procedure of the AE-HGNN framework

Input:

- News set  $N = \{n_1, n_2, \dots, n_t\}$
- User set  $U = \{u_1, u_2, \dots, u_m\}$
- User attribute matrix  $X$  (e.g., followers, friends, verified, activity)
- User-news interaction records  $R$  (to build hyperedges)
- Ground-truth labels  $Y$  for news (fake/real)
- Hyperparameters: learning rate  $\eta$ , epochs  $T$ , batch size  $B$

Output:

- Trained model parameters  $\Theta$
- Predicted labels  $\hat{Y}$  for news hyperedges

- 1: Initialize model parameters  $\Theta$  of AE-HGNN (semantic encoder  $M$ , hypergraph network, fusion layer, classifier)
- 2: Construct a hypergraph  $G = (V, E, X)$  from interaction records  $R$ 
  - Set  $V \leftarrow U$  (users are nodes)
  - For each news item  $n_i \in N$ , create a hyperedge  $e_i \in E$  connecting all users who interacted with  $n_i$
- 3: for epoch = 1 to  $T$  do
- 4:     Shuffle training news samples and form mini-batches of size  $B$
- 5:     for each mini-batch of news indices,  $I$  do
- 6:         // News semantic encoding
- 7:         Compute news embeddings  $Z_e = \{z_e(i) = M(n_i) \mid i \in I\}$

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```

8:
9:         // User credibility modeling via hypergraph learning
10:        Perform hypergraph convolution/attention on G to obtain user embeddings Ue = { u_j
| u_j ∈ U }
11:
12:        // Aggregate user embeddings for each news hyperedge in the batch
13:        For each news i ∈ I, aggregate embeddings of users in ei (e.g., mean/max/attention
pooling) to get u_i
14:
15:        // Feature fusion
16:        For each news i ∈ I, compute fused representation f_i = Concat(z_e(i), u_i)
17:
18:        // Classification
19:        Compute prediction ŷ_i = Softmax(W f_i + b)
20:
21:        // Loss computation
22:        Compute cross-entropy loss L = CE(ŷ_i, y_i) over all i ∈ I
23:
24:        // Backpropagation and update
25:        Update Θ using the Adam optimizer with learning rate η
26:    end for
27: end for
28: Return trained parameters Θ and predictions Ŷ

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## 5- Experiments

This section assesses the effectiveness of the proposed AE-HGNN framework using fake news benchmark datasets. We conduct the experiments to investigate the semantics of learning news and a hypergraph-based view on user credibility. Performance is reported along standard classification metrics so that direct comparisons with existing systems are possible.

### 5.1 Experimental Setup

All experiments were carried out in the deep learning framework PyTorch. To search for optimum parameters of models Adam optimizer, which converged stably in training of deep neural networks, was used. We used a fixed learning rate of 0.001 and defined the batch size as 64 for all datasets, due to the fact that we need to maintain identical training options across each dataset [33].

In this regard, we used four metrics generally used for evaluating performance: Accuracy, Precision, Recall, and F1-score to evaluate the proposed model's performance in detection. These metrics constitute a good holistic performance measure at the classification level because fake news detection tasks could have an imbalance. In particular, Accuracy is the uniform calibration of prediction accuracy, Precision is for how confident we are in predicting fake news, Recall means whether we can better sample fake, and F1-score balances between Precision and Recall [34].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (7)$$

$$Precision = \frac{TP}{TP+FP} \quad (8)$$

$$Recall = \frac{TP}{TP+FN} \quad (9)$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (10)$$

This section assesses the effectiveness of the proposed AE-HGNN framework using fake news benchmark datasets. We conduct the experiments to investigate the semantics of learning news and a hypergraph-based view on user credibility. Performance is reported along standard classification metrics so that direct comparisons with existing systems are possible.

## 5.2 Datasets Description

They evaluated their solution against two well-known benchmark datasets in fake news, PolitiFact and GossipCop, to assess the effectiveness of the solution proposed, Attention-Enhanced Hypergraph Neural Network (AE-HGNN). Datasets of this type have been widely leveraged in prior work to model user–news interaction networks, as they contain news content and social context information.

PolitiFact: A website that aggregates political news articles published on fact-checking websites and social media. They tagged it as fake or real, according to verified fact-checking sources. And it is not just articles and other textual content that it obtains, but user engagement data, such as comments and reposts, are also collected, as well as records of the user's interactions that can be used to build propagation structures for false information analysis. However, the GossipCop dataset is limited to entertainment articles only and has orders of magnitude more users and news items than PolitiFact. This dataset is dense interaction data of how news spreads across social media platforms, which might help when using the model to assess by merging together social context features [33][34].

Summary Statistics over the Used Datasets in Experiments. The overall distribution of the fake news samples and real news samples is shown in Table 2 as statistical descriptions of the training sets.

**Table 2. Statistical Summary of the Datasets**

Dataset	News	Users	Fake	Real
PolitiFact [35]	635	23,865	291	344
GossipCop [36]	10,546	72,384	4,642	5,904

## 5.3 Performance Comparison

In order to validate the effectiveness of the proposed Attention-Enhanced Hypergraph Neural Network (AE-HGNN) framework, we then conducted comparative experiments with several representative fake news detection networks such as TextCNN, Hierarchical Attention Network (HAN), BERT, and HyperGAT. Being the intermediate between Convolutional Networks and the attention / transformer-based family of language models, with a recently added graph neural network-based ones.

Results of the evaluation on the PolitiFact dataset are depicted in Table 3. As illustrated by the table, classical deep learning models (e.g., TextCNN and HAN) obtain medium performance levels, while transformer-based approaches (e.g., BERT) substantially enhance the accuracy of detection through contextual language representation.

Graph-based methods, like HyperGAT, boost the performance using social interaction structures. Even so, the expandable AE-HGNN model presents the optimal outcome of an accuracy of 0.98 and a value of F1-score at 0.97, which indicates that further removing information redundancy via combining hypergraph learning with attention mechanisms to represent high-order user–news relationships is effective here.

**Table 3. Performance comparison on the PolitiFact dataset**

Model	Accuracy	F1-Score
TextCNN	0.8	0.79
HAN	0.83	0.82
BERT	0.91	0.9
HyperGAT	0.94	0.93
AE-HGNN	0.98	0.97

Likewise, the performance comparison on the GossipCop dataset is reported in Table 4. In line with the results reported in PolitiFact data, the suggested AE-HGNN framework outperforms all baseline methods. This also shows that the derived structure of hypergraph-based relational modeling and attention mechanisms helps the suggested architecture to learn complex propagation patterns in social networks.

As seen in Table 5, the AE-HGNN model boasts an accuracy of 0.98 and an F1-score of 0.97, further substantiating the robustness and generalization ability of this method across diverse datasets.

**Table 4. Performance comparison on the GossipCop dataset**

Model	Accuracy	F1-Score
TextCNN	0.82	0.81
HAN	0.85	0.84
BERT	0.92	0.91
HyperGAT	0.95	0.94
AE-HGNN	0.98	0.97

#### 5.4 Ablation Study

To better understand the contribution of each component in the proposed AE-HGNN framework, we conducted an ablation experiment. This experiment is used to test the impact of different modules on model performance. Specifically, the attention module, the user credibility modeling module, and feature fusion were removed separately from the architecture. Table 5 shows the experimental results of the ablation study. Column removing any of the components causes a drop in classification accuracy, as demonstrated in the table. In particular, the lack of attention pattern leads to a decrease on capability of finding the most influential users in the propagation network. In a similar fashion, the omission of the user credibility modeling module limits the model to identifying behavioral patterns related to misinformation propagation. Additionally, without the feature fusion module to make full use of the information from textual and social contextual features, the detection performance. With the highest accuracy of 0.98, the full AE-HGNN model shows that fake news detection performance can be significantly increased through hypergraph learning, together with an attention mechanism combined with feature fusion.

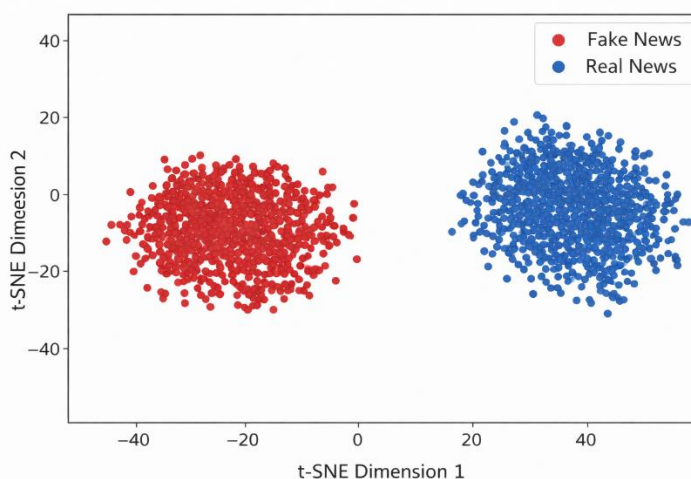
**Table 5. Ablation analysis**

Model Variant	Accuracy
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Without the attention module	0.95
Without credibility modeling	0.94
Without feature fusion	0.93
Full AE-HGNN	0.98

### 5.5 Visualization Analysis

In order to explore the representation ability of the proposed model, we visualized the news embeddings learned from the AE-HGNN framework via t-SNE (t-distributed Stochastic Neighbor Embedding). Using this technique, high-dimensional feature representations are compressed into a two-dimensional space that facilitates visual observation of the distribution of fake and real news samples. As shown in Figure 4, the visualization results. As illustrated in the figure, fake news and real news instances cluster into distinct groups within the embedding space. This shows the ability of our proposed AE-HGNN model to learn powerful feature representations that embed both semantic-aware and structural-aware semantics related to fake news propagation. The ten distinct clusters suggest that the framework can distinguish fake news from genuine news on social media networks.



**Figure 4. t-SNE visualization of news embeddings learned by AE-HGNN**

### 5.6 Discussion

In this section, the experimental results demonstrate that the proposed AE-HGNN performs far better than existing methods in terms of fake news detection for the readers. Both PolitiFact and GossipCop datasets' performance comparisons of the proposed model to several representative baseline methods, including CNN-based, attention-based, transformer-based, and graph neural network-based methods, consistently outperform these baseline methods. The results of the proposed framework show up to 98% accuracy, which indicates that combining textual semantic information with social interaction patterns can certainly enhance fake news detection performance. The second crucial reason for the high performance of the AE-HGNN model is relational modeling based on a hypergraph. Traditional graph neural networks model the edges pairwise, meaning that there is an edge for every two nodes connected directly by a relationship. However, hypergraphs allow us to connect multiple users at once with the same hyperedge. It can help the model study high-order interactions between users who took part in spreading a single news article, better describing information dissemination dynamics on social networks. The proposed framework extracts influential users in the propagation network, which is mainly based upon attention mechanism [37].

An attention module is used where the weights are given more importance to users with a stronger influence or authority, thus allowing the model to focus on useful interactions for improving representation learning and classification accuracy [38].

In addition, the user credibility modeling module that aims to remove suspicious accounts from users' reliability would also be equally critical. Follower count, verification status, and activity patterns are rich behavioral signals to determine the dissemination pattern of disinformation. An ablation study is used to provide proof of effectiveness. The final feature fusion mechanism fuses semantic representations of news text with user person-life structure information. This approach also results in a more robust detection with respect to fake news over different datasets, as it allows the model to encode both content-level information as well as social context features.

The large margin over previous methods once again highlights the effectiveness of the AE-HGNN framework for modeling user–news relations and demonstrating high-quality results in fake news detection on online social networks.

## 6- Conclusion

The authors of this paper suggested that the Attention-Enhanced Hypergraph Neural Network (AE-HGNN) be used for fake news detection within online social networks. It classifies the news articles considering their complex interaction with users in a hypergraph-based relational learning approach, and integrates textual semantic representations with user credibility modeling. The Attention mechanism enhances the model by focusing on influential users in the propagation network.

We conduct experimental evaluations on the PolitiFact and GossipCop datasets, which show that the proposed model significantly outperforms multiple baselines, achieving accuracy as high as 98%. The findings confirm that hypergraph learning with social context information significantly improves fake news detection performance.

Going forward, our focus will be on multimodal fake news detection, the monitoring of misinformation in real time, and testing the proposed framework over large-scale social media tools.

## Conflicts Of Interest

The author declares no conflict of interest.

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