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REVIEW PAPER

An Attention-Based Hypergraph Neural Network for Fake News Detection: Design, Analysis, and Performance Evaluation

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***Abstract*—The accelerating development of social media has largely contributed to the spread of fake news, presenting critical problems to social credibility and the stability of society. Conventional detection methods usually do not reflect the multifaceted association between users, posts, and news content. The paper introduces an attention-based Hypergraph Neural Network (HGNN) to detect fake news based on the UPFD dataset. In contrast to traditional graph-based models, which only describe pair-wise relationships, the proposed model uses hypergraphs to describe higher-order interactions among many entities. The attention mechanism is incorporated in the model so that it can give more priority to various hyperedges, which enhances the learning of the features and the classification. The experimental findings prove that the proposed scheme is more accurate, more precise, more recall, and has a higher F1-score than the traditional machine learning models and regular Graph Neural Networks (GNNs). A comprehensive analysis of the model's efficacy, constraints, and potential future applications is also included in this work.**

Keywords*—Fake News Detection, Deep Learning, Graph Neural Networks, Social Media, Misinformation, NLP.

I. Introduction

The digital communication technologies and social media platforms have grown exponentially and have changed how information is produced, exchanged and consumed. Social media like Twitter (X), Facebook, and Instagram allow users to share information in real time with an international audience. Though this accessibility has made information sharing democratic, it has also led to the rapid spread of fake news fake or fabricated information with the intention to influence the masses, generate engagement, or disrupt. The problem of fake news has become a critical issue in modern society and has influenced the spheres of politics, health, and social stability. Events like elections and global emergencies have proven how misinformation can rapidly disseminate and influence masses of people. The viral nature of social networks, whereby information is disseminated through complex user networks, is also contributing to this problem, often without any measure of verification. Moreover, the fact that echo chambers and content recommendations operate on algorithms solidifies the beliefs that people have, which predisposes them to misinformation.

Content-based methods are the most widespread conventional approaches to detect fake news based on textual indicators such as writing style, sentiment, and linguistic patterns. Although such approaches can be helpful, they frequently do not reflect the wider picture, within which information dissemination occurs. To overcome this shortcoming, graph models have been proposed, with the connections between users, posts, and news articles being represented as networks. Specifically, Graph Neural Networks (GNNs) have succeeded in achieving high performance using structural data and propagation patterns.

Nevertheless, the generic GNNs are inherently restricted to pair-wise relationships between nodes, which limits them to more complex interactions in social networks. In practice, the dissemination of fake news can be a large number of users of the same content at the same time, which can be represented in higher-order relationships, which are not effectively represented with the help of the classical graph structures.

To address these drawbacks, this paper presents an Attention-Driven HGNN to detect fake news. In contrast to traditional graphs, hypergraphs permit a hyperedge to have many nodes, which can be used to model group-level interactions between users, posts and news articles. The model's capacity to identify and prioritize the most significant interactions in the network is further enhanced by including an attention mechanism.

A. Contribution of Paper

The key findings from this study are as follows:

- Creation of a hypergraph-based model to capture higher-order interactions in the spread of fake news.
- Combination of an attention mechanism to enhance feature aggregation and representation learning.
- Thorough analysis of the proposed model with the help of the UPFD dataset.
- Comparison of performance showing that it is better compared to traditional machine learning and graph-based methods.

In general, the suggested study will provide a highly effective and scalable false news detector through a combination of the advantages of hypergraph modeling and attention mechanisms. The proposed methodology not only enhances the accuracy of detection but also gives an additional insight into the complex processes of misinformation spread in online social networks.

II. Background and Motivation

The problem of identifying fake news has been discussed by many researchers in the recent years as the influence of

online sources on the formation of the public opinion increases. One has to know the history of this problem and the inefficiency of the existing approaches in order to develop more effective detection models. The section gives a short description of the key concepts related to fake news detection, graph-based learning, and hypergraph modeling and then rationalizes the proposed approach.

A. Fake News Detection

Fake news detection is a technology that attempts to identify automatically whether a news article or information is real or fake. Early research on this field was largely devoted to the analysis of textual data in the form of linguistic characteristics such as writing style, sentiment, and frequencies of words. The methods were founded on traditional machine learning algorithms and human-designed features. However, with social media, fake news is not limited to text manipulation. It may be complex interactions among users, e.g. sharing, commenting, reposting. Therefore, one cannot have a complete picture of misinformation propagation with just content-based features. This has witnessed introduction of context-sensitive strategies that consider content and social interactions.

B. Graph Neural Networks (GNNs)

Graph Neural Networks (GNNs) emerged to be an effective instrument in modeling relational data. GNNs are employed to identify fake news by considering users, posts, and news articles as nodes and exchanges between them, such as sharing and commenting, as edges. The message passing process that GNNs resort to involves information pooling between neighboring nodes to learn meaningful representations. It has been demonstrated that GNN-based methods are superior to traditional methods because they can capture the propagation patterns and social context. They come in particularly convenient regarding identifying the proliferation of fake news within networks. However, the traditional GNNs are only able to connect two node relationships i.e., each edge can have only two nodes. This constraint makes it more difficult to describe more complex interactions between multiple users and content simultaneously.

C. Hypergraph Representation

Hypergraphs have been proposed to address the shortcomings of traditional graphs, as a more expressive data structure. A hyperedge in a hypergraph may have more than one node, and it is possible to model higher-order relationships. This applies especially in social networks, whereby a group of users can be able to access the same piece of news simultaneously. Hypergraph modeling allows a more realistic description of real-world interactions by modeling group dependencies. As an example, multiple users on the same news article may be modeled as a single hyperedge, maintaining the relationship between them. This more detailed representation offers greater informational content to fake news detection.

D. Need for Attention Mechanism

Although hypergraphs enhance the modeling of complex relationship, not every interaction is equally important to fake news detection. Certain users or interactions can have more important information than others. So, there should be a distinction between essential and unessential connections. Attention mechanisms deal with this problem by giving weights to various nodes or hyperedges depending on their significance. This allows this model to focus on the most relevant information during the aggregation of features, increasing the learning process and accuracy of the prediction.

Current methods of fake news detection have several limitations since content-based approaches lack social interactions, traditional graph models focus only on pairwise relationships, and lack of emphasis on key interactions decreases overall performance. This paper seeks to offer a solution to these issues by introducing an attention-based hypergraph neural network that incorporates higher-order relationship modeling using hypergraphs and selective information aggregation using attention mechanisms by merging the two notions, which should in turn offer a more profound and precise solution to fake news detection. It not only captures the structural complexity of social networks but also highlights the most influential interactions, resulting in better detection performance.

III. Realted Work

Ujun Jeong et al. [1] presented a model based on hypergraphs that models group interactions on news using a dual-level attention mechanism; this model performed very well on benchmark datasets. Ujun Jeong et al. [2], introduced BlueTempNet, a dataset that depicts the time-based behavior of user engagement across many social networks; this will be useful for future behavior research and data collecting. Wenbo Zheng et al. [3] put out a multimodal framework called Hypergraph-Enhanced Graph Reasoning to handle the problems with intra- and inter-modality, improving the capacity to detect false news via the use of contextual graph representations. Chenzi Zhang et al. [4] used a sub-gradient strategy to speed up performance and returned to hypergraph-based semi-supervised learning with a focus on unlabeled data confidence intervals. Pei-Cheng Li and Cheng-Te Li [5] presented the TCGNN, which streamlines the procedure for detecting false news by grouping texts together to strengthen their semantic representation. Benkuan Cui et al. [6] introduced the Intra-graph and Inter-graph Joint Information Propagation Network (IIJIPN), which use attention and third-order text graph tensors to identify false information across several datasets. Junfei Wu et al. [7] introduced GETRAL, a graph-based system that uses contrastive learning to understand the more distant semantic relationships between evidence and assertions. Xing Su et al. [8] introduced Us-DeFake, a model that uses user credibility signals to improve fake news identification; their Hy-DeFake model [10] uses attributed hypergraphs to understand high-order user-news interaction. Xiangguo Sun et al. [9] shown its efficacy in the study of sociological phenomena by introducing a hypergraphic framework for assessing social impact with more intricate patterns of interaction.

Ling Sun et al. [11] and Nikos Salamanos et al. [12] both suggested hypergraph-based models (HG-SL and Hyper-GraphDis) that study user behavior and enhance the scalability and accuracy of detecting false news, especially in early-stage detection tasks.

TABLE I. COMPARISON OF GNN METHODS

Author(s)	Method/Model	Key Features	Results/Performance
Ujun Jeong et al. [1]	Hypergraph model with dual-level attention	Employs attention mechanisms and hypergraphs to model group interactions in news; pre-computed features are used for both users and news.	Performs well with less labeled data while enhancing privacy and replicability.
Ujun Jeong et al. [2]	BlueTempNet	Captures temporal user interactions and incorporates various network kinds, such as user-to-community relationships.	Allows you to analyze previous and prospective social interactions via Bluesky Feeds.
Wenbo Zheng et al. [3]	Hypergraph-Enhanced Graph Reasoning	Graph Self-Attention Enhancement models interactions between and within modalities using multimodal hypergraphs.	Outperforms state-of-the-art methods in multimodal graph reasoning.
Chenzi Zhang et al. [4]	Semi-supervised learning using hypergraphs	Faster performance is achieved by using the subgradient approach, and for unlabeled data, there is a convex program with confidence intervals.	Outperforms existing semi-supervised methods in large-scale datasets.
Pei-Cheng Li et al. [5]	Text-Clustering Graph Neural Network (TCGNN)	Text clustering investigates correlations within text for FND and is used to identify representative words.	Superior performance compared to existing GNN-based models.
Benkuan Cui et al. [6]	Intra-graph and Inter-graph Joint Information Propagation Network (IIJIPN)	Third-order Text Graph Tensor for propagation inside and across graphs; sequential, syntactic, and semantic aspects.	Outperforms state-of-the-art methods across four public datasets.
Junfei Wu et al. [7]	GETRAL (Graph-based sEmantic structure mining)	Models assertions and evidence as graph-structured data; uses adversarial data augmentation and supervised contrastive learning.	Enhanced FND with better semantic dependency capture.
Xing Su et al. [8]	Us-DeFake	User credibility and news characteristics are represented by dual-layer subgraphs, as are user-aware news embeddings.	Superior at leveraging user credibility signals for FND.
Xiangguo Sun et al. [9]	Hypergraph-based sociological model	Combines hypergraph and line graph capabilities to capture complex interaction patterns for use in sociological behavioral study.	Excellent performance in determining social conformance, equivalency, environmental change, and polarization.
Xing Su et al. [10]	Hy-DeFake	Hypergraph with attributes for high-order user-news connections; indications for user credibility in FND.	Excellent results on four different real-world datasets; rich patterns of user interaction seen in groups who engage in fake news.
Ling Sun et al. [11]	HG-SL	User behavior is the only basis for both self-attention-based local context learning and hypergraph-based global interactivity.	Outperforms state-of-the-art methods in early-stage FND.
Nikos Salamanos et al. [12]	Hyper-GraphDis	Scalable and fast analysis of Twitter data using hypergraphs for misinformation detection.	F1 scores and accuracy have significantly improved, particularly for datasets that are unbalanced.
V. Karuna et al. [13]	GNN for fine-grained fake news classification	Canonical polyadic (CP) decomposition of a third-order co-occurrence tensor representing sentence connections inside news articles.	The accuracy rate of GNN was 99%, and it is possible to obtain 100% using ensemble approaches.
Alpana A. Borse et al. [14]	HA2_HC_FNP_NN	Integrates Hypergraph Attention, Hierarchical Attention, and Hypergraph Convolution to extract richer document features.	Tested on LIAR dataset; significantly improves accuracy for short news content.
Alaa Safaa Mahdi & Narjis Mezaal Shati [15]	Review of GNN-based FND systems	Comprehensive review of GNN techniques and datasets used in FND.	Offers suggestions for future lines of inquiry and the creation of sophisticated models.
Litian Zhang et al. [16]	DGA-Fake	Propagation path generation with a guided diffusion module for early FND.	Outperforms existing methods in early FND across three datasets.

Overall, these papers demonstrate state-of-the-art methods, relying on hypergraphs, GNNs, and multimodal features to enhance the effectiveness and accuracy of fake news detection. The overview of the complete article in various parameters such as methodology used, their properties and performance Previous studies Comparison of the FND models based on GNNs is presented in Table I. The studies below provide better practices that harness hypergraphs, GNNs, and multimodal techniques to enhance the precision and efficiency of FND.

IV. PROPOSED METHODOLOGY

The suggested solution aims at converting the conventional graph-based models into a hypergraph format in order to more effectively represent the intricate relationships among users, posts and news items in the UPFD dataset. The hypergraph formulation, as opposed to the conventional graph, can be used to model higher-order relationships: two users sharing the same news are connected in a higher-order relationship and grouped under the same hyperedge.

Fig. 1 is a simplified structure of the proposed model, which shows parallel learning of features through semantic and credibility channels. The combination of these features via a fusion mechanism and their passage to a classifier to make final decisions enhances the effectiveness of the fake news detection.

A. Hypergraph Construction

The data set of the UPFD is first dealt with in order to get the interaction data between users and news articles. To model user-user relations and their interactions with news content, a weighted edge matrix is created. This graph is then transformed into a hypergraph by grouping similar nodes into hyperedges, according to common interactions. The resulting hypergraph G=(V,E) is input to the model, with V corresponding to nodes (users and news articles) and E corresponding to hyperedges modeling interactions among the groups. This transformation enables a descriptive representation of the social behavior compared to the traditional graph representations.

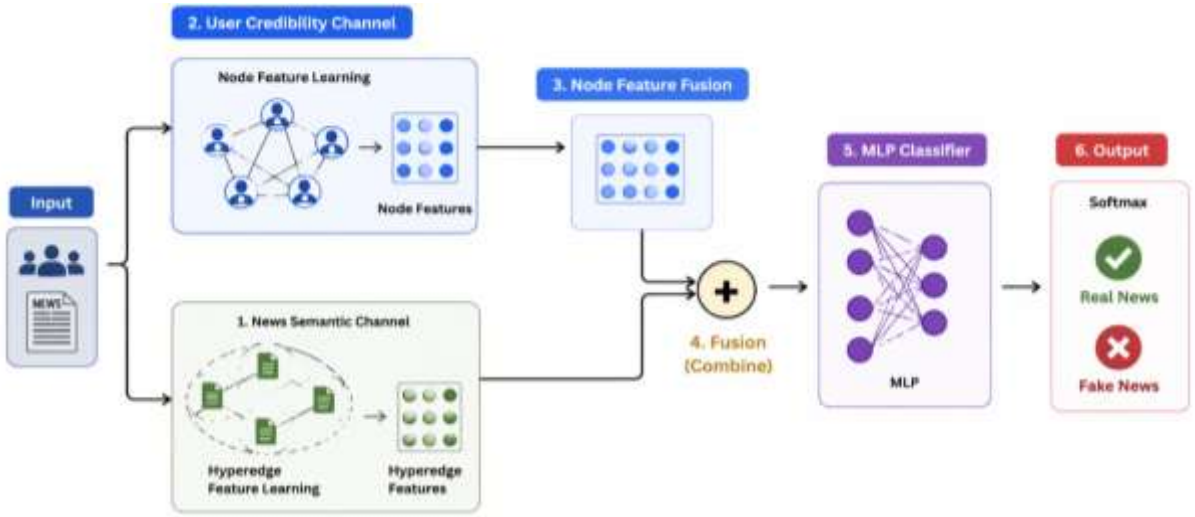

Fig. 1. Workflow of Proposed Methodology

B. *Dual-Channel Feature Learning*

To achieve the best capture of semantic and behavioral information, the proposed model uses a dual-channel learning approach whereby the News Semantic Channel is used to obtain meaningful representations of the news content by processing textual features, and encodes them into hyperedge representations, whereas the User Credibility Channel can be used to model user behavior and credibility by modeling credibility features through an unsupervised hypergraph-based autoencoder to learn higher-order relationships between users influence.

C. *Feature Fusion Mechanism*

Following feature extraction on two channels, a mutual information-based fusion module integrates semantic and credibility information by summing node features of users attached to each news article to obtain representative embeddings, thus allowing the model to integrate heterogeneous information sources, interactions between users and content, and enhance discriminative feature learning.

D. *Attention-Driven Hypergraph Learning*

These fused features are then fed into a customized HAN that adds an attention mechanism to weight importance to each hyperedge and allow the model to concentrate on the most influential interactions, decrease the influence of noisy or irrelevant connections, and enhance feature propagation across the hypergraph to selectively aggregate features, thus increasing overall detection performance.

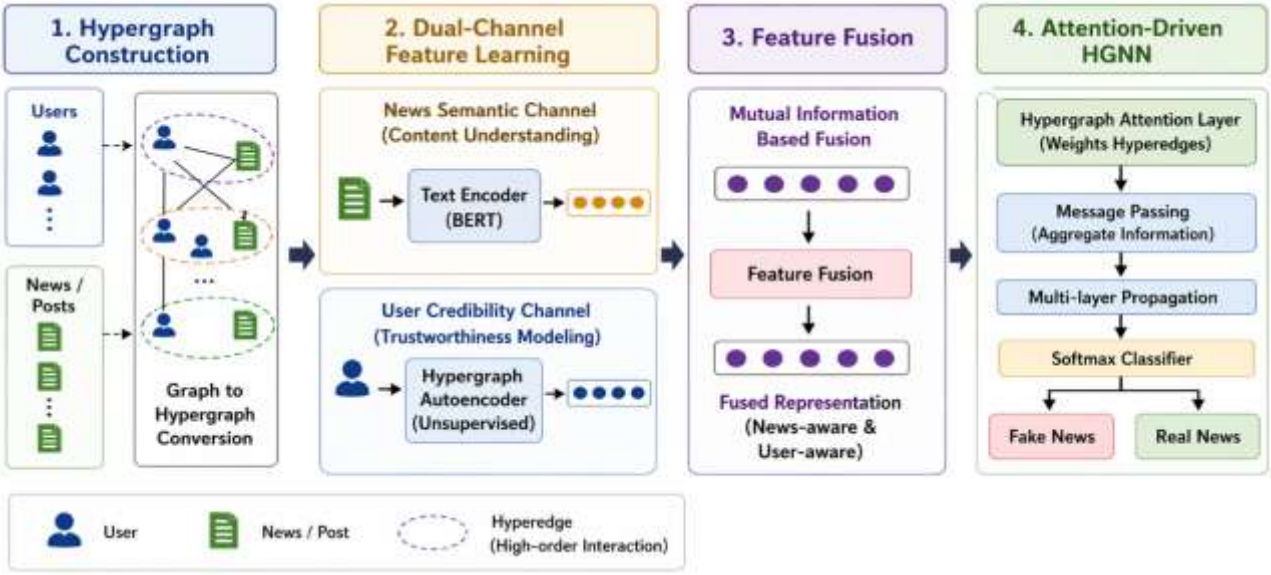

Fig. 2. Architecture of Proposed Methodology

E. *Model Architecture*

The architecture that has been proposed and displayed in Fig. 2 has the following layers. Fig. 2 illustrates the overall end-to-end pipeline of the proposed methodology, with the user interactions and news content being converted to a hypergraph format. The semantic and credibility features are acquired in independent channels, combined, and processed through an attention-based HGNN to attain precise fake news classification.

Embedding Layer- Produces preliminary feature representations of nodes. BERT is the model that is used to obtain news content embeddings and profile and interaction data are used to obtain user features.

- **Hypergraph Attention Layer-** Assigns hyperedge weights, allowing the model to focus on significant relationships when aggregating features.
- **Message Passing Layer-** Propagates features iteratively through nodes linked by hyperedges, higher-order dependencies.
- **Output Layer-** A softmax classifier is used to predict whether a news article is fake or real.

V. Implementation and Results

The proposed Attention-Based HGNN is applied to the UPFD (User Propagation Fake News Detection) dataset which includes the data on user interactions, news articles and propagation patterns extracted on platforms such as Twitter. This dataset consists of user activity, sharing behaviour, and related metadata, which allows to effectively model the real-world misinformation spread.

A hypergraph is generated to model the complex relationships between users and news content, where the nodes are users, posts, and news articles and the hyperedges are group interactions, such as two or more users sharing or interacting with the same content. An incidence matrix mathematically represents these relationships and forms the basis of hypergraph-based learning.

Several layers make up the proposed HGNN architecture, and their purpose is to extract and propagate relevant characteristics. The first thing to do is utilize an embedding layer to get node representations in low dimensions. The next step is an attention mechanism that allows the model to focus on the most important interactions by assigning significance weights to hyperedges. Then, a message-passing layer collects information of neighboring nodes having hyperedges, and it facilitates the propagation of features in the network. Lastly, a softmax classification layer is employed to classify news articles as fake or real. This model is trained with binary cross-entropy loss and Adam optimizer.

A. Training Performance

The training behavior is performed on 200 epochs and the learning behavior is shown in Fig. 3. In the first training stage, training loss and validation accuracy exhibit fluctuations as the model adapts. Nevertheless, at around 100 epochs, the model becomes stable, and the training loss is reduced considerably. At the conclusion of training, the model has training Accuracy of 90.32 %, and training Loss of 0.0157. This signifies efficient convergence and learning of meaningful representations.

B. Testing and Validation

Testing with the same configuration is done to confirm the generalization ability of the model. Fig. 4 illustrates that there are minor differences in loss and accuracy in the testing phase as a result of imbalanced datasets. Nonetheless, training and validation loss are not significantly different, which points to an optimized model. This enhanced performance can be explained by the attention mechanism that assists the model focus on important hyperedges at the beginning of the training process. This leads to better feature learning and weight optimization. The confusion matrix (Fig. 5) also indicates that the model is effective, with a very low misclassification rate. The model has a validation Accuracy of 92 and a validation Loss of 0.0120.

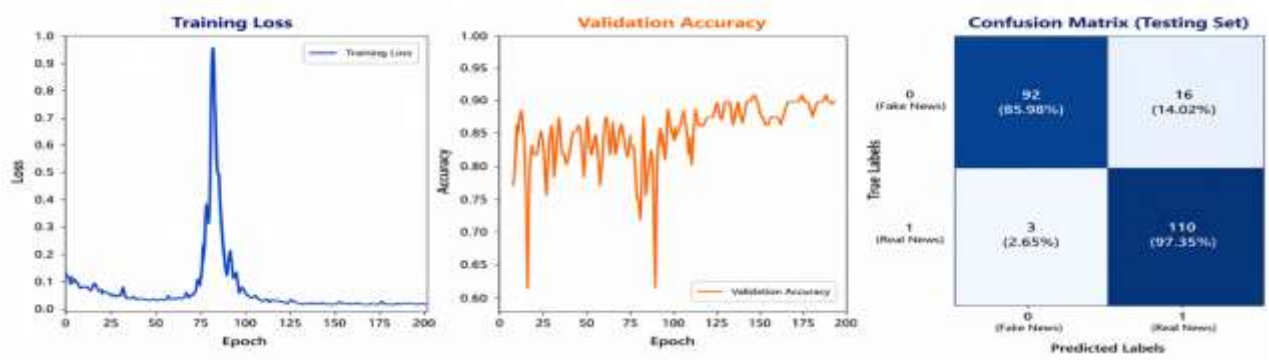

Fig. 3. Training results

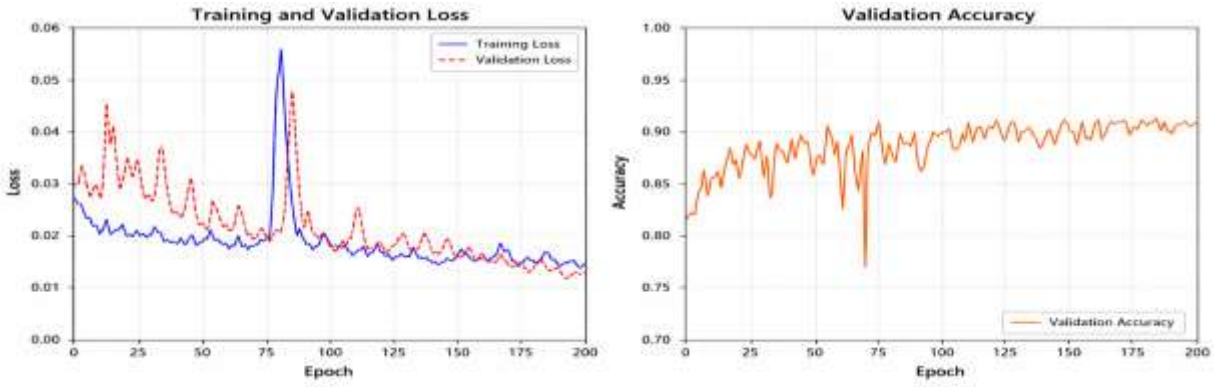

Fig. 4. Testing results on real set of news

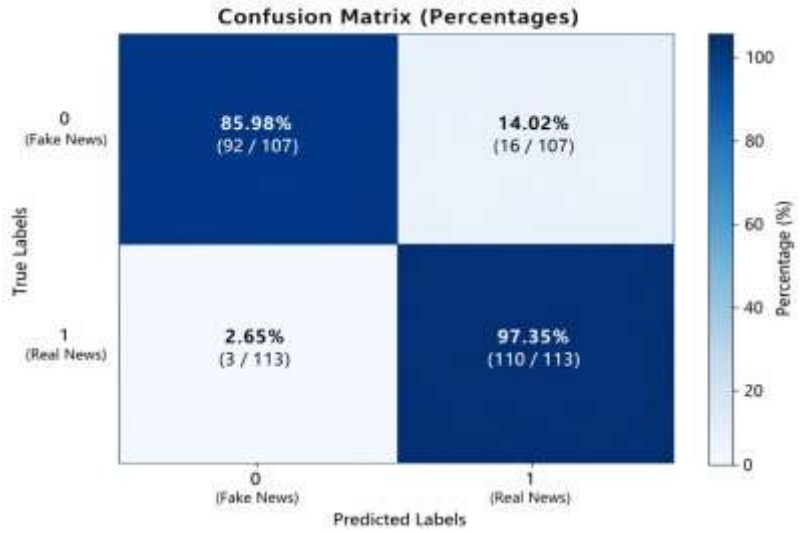

Fig. 5. Confusion matrix on Testing Dataset

C. *Comparative Analysis*

It is possible to gauge the efficacy of the suggested method by comparing the HGNN model with several baseline models, such as GNNs, RF, and LR. The results, summarized in Table II, show a clear improvement in performance as model complexity increases:

TABLE II. RESULT COMPARISON OF PROPOSED METHOD

Metric	LR	RF	GNN	Proposed Method
Accuracy	77.80%	83.20%	88.10%	92.60%
Precision	76.90%	81.40%	86.30%	90.10%
Recall	73.50%	80.20%	84.10%	88%

Table II explicitly reveals that the proposed HGNN model has a better performance index than both the traditional machine learning methods and the standard graph-based models. The HGNN model can be explained by the fact that it is able to learn higher-order relationships among users and news articles that cannot be well-modeled by the traditional GNNs. Also, the attention mechanism is incorporated which improves the ability of the model to concentrate on significant interactions resulting in a higher classification accuracy.

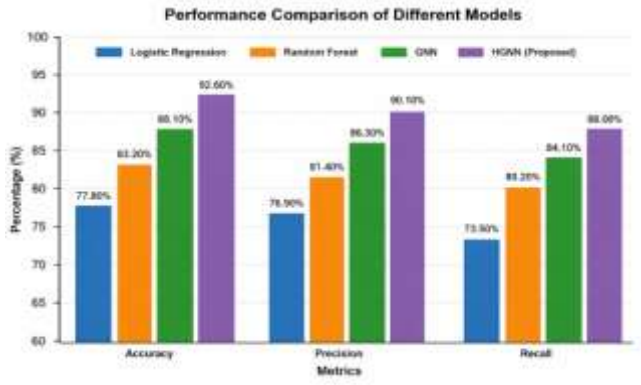

Fig. 6. Performance Comparison of FND

Fig. 6 compares the various models in terms of accuracy, precision and recall and shows how the proposed HGNN model outperforms the traditional and graph based models.

VI. CONCLUSIONS

This study presents a framework of attentions based Hypergraph Neural Network (HGNN) that can effectively detect fake news by exploiting higher-order relationships between users, posts, and news articles. The proposed model, in contrast to usual machine learning and typical graph-based methods, models the complex group interactions via hypergraph forms and improves feature learning with an attention mechanism. This allows the model to prioritize the most influential relationships in the network, resulting in higher classification performance. Experimental analysis on the UPFD dataset shows that the HGNN model performs significantly better than baseline models, including LR, RF and standard GNNs in various performance metrics, including accuracy, precision, recall, and F1-score. The findings affirm the fact that the use of higher-order relational information and attention-based weighting is a highly beneficial factor in enhancing the detection of fake news. Although effective, the model has some limitations, such as increased computational complexity and reliance on the quality of interaction data. Also, scalability can be an issue in the case of very large social networks. Further research on the model can be done to enhance scalability and efficiency, to incorporate multimodal data like images and videos, and to create explainable AI methods to improve the transparency of the model. Furthermore, the framework can be further applied to the real-time fake news systems of detection of fake news on a variety of platforms to make it even more accessible to practice.

REFERENCES

[1] Jeong, Ujun, et al. "Nothing stands alone: Relational fake news detection with hypergraph neural networks." 2022 IEEE International Conference on Big Data (Big Data). IEEE, 2022.

[2] Jeong, Ujun, et al. "BlueTempNet: A Temporal Multi-network Dataset of Social Interactions in Bluesky Social." arXiv preprint arXiv:2407.17451 (2024).

[3] Zheng, Wenbo, et al. "Two heads are better than one: Hypergraph-enhanced graph reasoning for visual event ratiocination." International Conference on Machine Learning. PMLR, 2021.

[4] Zhang, Chenzi, et al. "Re-revisiting learning on hypergraphs: confidence interval and subgradient method." International Conference on Machine Learning. PMLR, 2017.

[5] Li, Pei-Cheng, and Cheng-Te Li. "TCGNN: Text-Clustering Graph Neural Networks for Fake News Detection on Social Media." Pacific-Asia Conference on Knowledge Discovery and Data Mining. Singapore: Springer Nature Singapore, 2024.

[6] Cui, Benkuan, et al. "Intra-graph and Inter-graph joint information propagation network with third-order text graph tensor for fake news detection." Applied Intelligence 53.16 (2023): 18971-18988.

[7] Wu, Junfei, et al. "Adversarial contrastive learning for evidence-aware fake news detection with graph neural networks." IEEE Transactions on Knowledge and Data Engineering (2023).

[8] Su, Xing, et al. "Mining user-aware multi-relations for fake news detection in large scale online social networks." Proceedings of the sixteenth ACM international conference on web search and data mining. 2023.

[9] Sun, Xiangguo, et al. "Self-supervised hypergraph representation learning for sociological analysis." IEEE Transactions on Knowledge and Data Engineering 35.11 (2023): 11860-11871.

[10] Su, Xing, et al. "Hy-DeFake: Hypergraph Neural Networks for Detecting Fake News in Online Social Networks." arXiv preprint arXiv:2309.02692 (2023).

[11] Sun, Ling, et al. "Hg-sl: Jointly learning of global and local user spreading behavior for fake news early detection." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 37. No. 4. 2023.

[12] Salamanos, Nikos, et al. "HyperGraphDis: Leveraging Hypergraphs for Contextual and Social-Based Disinformation Detection." Proceedings of the International AAAI Conference on Web and Social Media. Vol. 18. 2024.

[13] V.KARUNA, et al. “Fake News Classification Using Tensor Decomposition and Graph Convolutional Network.” International Journal of Advanced Research in Science and Technology IJARST, Volume 14, Issue 04, Apr 2024

[14] Borse, Alpana A., and G. K. Kharate. "Design Fake News Prediction-Classification using 4 HAN and Hypergraph–Neural Network." International Journal of Computer Science and Information Security (IJCSIS), 2022

[15] Mahdi, Alaa Safaa, and Narjis Mezaal Shati. "A Survey on Fake News Detection in Social Media Using Graph Neural Networks." Journal of Al-Qadisiyah for Computer Science and Mathematics 16.2 (2024): 23-41.

[16] Zhang, Litian, et al. "Mitigating Social Hazards: Early Detection of Fake News via Diffusion-Guided Propagation Path Generation." ACM Multimedia 2024.

