Attention-Driven Graph Neural Network Architecture for Accurate Detection of Fake News

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Abstract. *The widespread dissemination of fake news on social media presents a significant challenge in today's digital era, calling for intelligent and scalable detection models. Traditional machine learning and deep learning techniques often fail to capture the complex relational structures inherent in misinformation spread. This paper explores two advanced graph-based approaches—Attention-enhanced Graph Neural Networks (GNNs) and Hypergraph Neural Networks (HGNNs)—using the UPFD (User Profile Fake News Detection) dataset. The first model leverages attention mechanisms in GNNs to dynamically weigh contextual node relationships, improving accuracy, precision, recall, and F1-score. It also incorporates preprocessing strategies like node preparation and retweet handling to mitigate overfitting, especially in long training cycles. While effective on UPFD, models like GraphSAGE show promise on larger datasets such as Gossipcop, highlighting the need for scalable solutions. The second approach introduces an HGNN framework that models higher-order interactions among users, posts, and news articles using hyperedges and incidence matrices. This structure allows for richer feature extraction and, when combined with attention, further enhances performance over traditional GNNs and other baseline models. These findings underline the value of capturing both local and global relationships in fake news detection and point toward future improvements in feature mapping, scalability, and multilingual adaptability.*

Keywords: *Fake News Detection, Machine Learning, Attention Based GNN, Neural Network, RNN*

Introduction

The Internet has revolutionized communication, offering low-cost and rapid information sharing. As a result, social media has become a dominant source for news consumption, overtaking traditional newspapers. While these platforms offer convenience, they also enable the widespread and rapid dissemination of fake news and misinformation. Such false content, especially during sensitive events like elections or pandemics, can severely impact public opinion and social stability.

Fake news detection involves verifying the authenticity of news content and classifying it as real or fake. This task is complex due to the presence of varied contextual and relational data, including users who interact with the news and other articles on similar topics. Existing detection methods can be broadly categorized into two types:

1. Pattern-based approaches**-** It focuses on analyzing textual patterns within the news. Some models incorporate user feedback (likes, shares, comments), while others explore sentiment biases, assuming that fake news often carries emotionally charged content.

2. Evidence-based approaches- It validates news by comparing claims with external evidence sources such as knowledge graphs or fact-checking websites. These models employ semantic similarity analysis and often use attention mechanisms to highlight important text segments for classification.

Machine learning-based fake news detection typically involves stages such as data collection, preprocessing, feature extraction, model training, and evaluation. Recent advancements integrate attention mechanisms and deep learning models like Graph Neural Networks (GNNs) to better capture relational and contextual cues across news and user networks. The General Flowchart for fake news detection using GNN is shown in Figure 1.

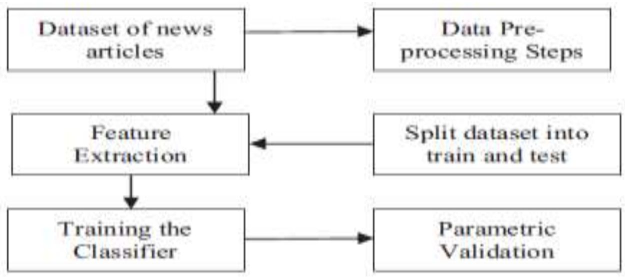


Fig.1. General Flowchart for fake news detection

Graph neural networks (GNNs)

Graphs are effective for modeling data in domains like social media, the internet, and chat services. Graph Neural Networks (GNNs) are powerful tools for prediction and classification in such graph-structured data. They generate embedding vectors for each node, capturing both function and position, which are then used for downstream predictions as shown in figure 2. GNNs operate through neighborhood aggregation—each node updates its embedding by aggregating features from neighboring nodes.

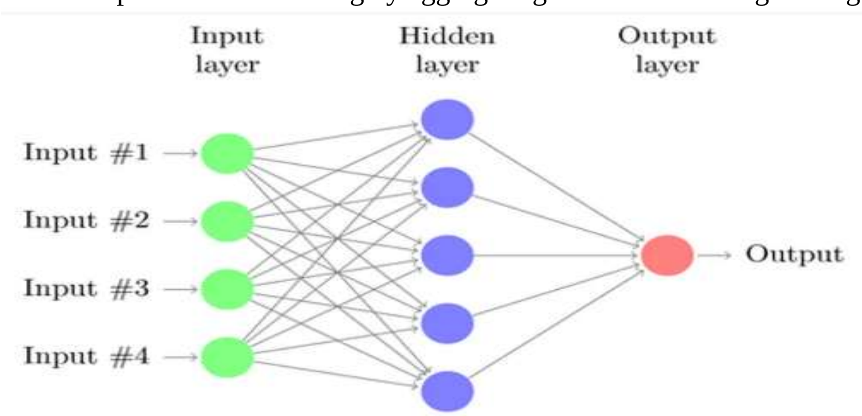


Fig.2. A Basic Architecture of a GNN

The GCN model uses mean-pooling while GraphSAGE applies max-pooling or LSTM-based aggregation which enables inductive learning. While traditional GNNs capture pair-wise relationships, heterogeneous GNNs enhance expressiveness by incorporating various node and edge types. GNNs have also excelled in tasks like text classification, recommendation systems, and sentiment analysis due to their ability to learn long-distance dependencies. In fake news detection, GNN-based methods are typically classified into pattern-based approaches—focusing on text patterns and social signals—and evidence-based approaches that compare claims with verified sources or knowledge graphs.

Attention-Based GNNs

Attention-based Graph Neural Networks (GNNs) represent a significant advancement in graph representation learning by enabling models to focus selectively on the most relevant nodes or edges within a graph. This selective focus is especially beneficial for complex applications like fake news detection, where the relationships between users, content, and interactions are often intricate and noisy. Inspired by human cognition—where attention highlights the most significant stimuli—attention mechanisms in GNNs help determine which components of the graph are most influential during the message-passing or neighborhood aggregation phase. One of the core elements is the attention score, which quantifies the influence of neighboring nodes or edges. These scores are learned during training and may be based on various inputs, such as node features, edge properties, or network context.

Self-attention is a widely used form of this mechanism, especially in Graph Attention Networks (GATs), allowing a node to weigh its neighbors' contributions based on the relevance of their features. Edge-level attention further enriches this approach by incorporating edge attributes, which enables more granular modeling of relationships—such as assessing credibility in social networks.

The benefits of integrating attention in GNNs include:

- Adaptive Weighting- The model dynamically assigns importance to different parts of the graph, outperforming static aggregation methods.
- Noise Resistance- By concentrating on significant signals, attention-based GNNs are more robust to irrelevant or misleading data.
- Transparency- Attention scores offer insights into the model's reasoning, improving interpretability.
- Scalability- Despite their complexity, many attention-based GNNs remain computationally efficient and scalable to large datasets.

This framework thus holds strong potential for tasks requiring deep analysis of structured yet heterogeneous data.

Contribution of the Work

This study introduces attention-driven Graph Neural Network (GNN) and Hypergraph Neural Network (HGNN) architectures for accurate fake news detection on social media. The models leverage attention mechanisms to dynamically focus on relevant contextual and relational information, enhancing feature representation and classification performance. By modeling both pairwise and higher-order interactions among users, posts, and articles, the HGNN effectively captures complex social dynamics that traditional models overlook. The proposed framework is evaluated on benchmark datasets like UPFD and GossipCop, outperforming conventional machine learning models and existing GNN variants in accuracy, precision, recall, and F1-score. Additionally, the study addresses overfitting through optimized node representation and training strategies, and enhances adaptability through advanced feature and profile mapping. This work also explores the models' scalability, real-world applicability, and future extensions, such as real-time detection, multilingual support, and user credibility scoring, offering a robust foundation for advanced misinformation detection systems.

Literature Review

Table 1 collectively emphasize the potential of graph-based and attention-driven architectures for improving fake news detection, highlighting progress in multi-modal data modeling, early detection, and real-time application readiness.

Table 1: A Comparative Survey of Graph-Based and DL Techniques for FND

Ref.	Author(s)	Method/Model	Dataset(s)	Key Contributions/Outcomes
[1]	Fahim Belal Mahmud et al.	ML algorithms vs. GNN (PyG, DGL)	UPFD	GNN outperforms traditional ML on text + graph-structured data
[2]	Gunawansyah et al.	LSTM + Android App	Not specified	LSTM achieved 98.3% accuracy; no under/overfitting observed
[3]	Kayato Soga et al.	Graph Transformer Network (GTN)	FibVID, Twitter	Detects stance similarity; enhances propagation-based fake news detection
[4]	Nida Aslam et al.	Bi-LSTM-GRU + Dense Ensemble	LIAR	Achieved ~91% F1-score; outperforming prior LIAR-based methods
[5]	Yingtong Dou et al.	UPFD Framework (Graph + Content)	Politifact, others	Showed content + propagation modeling is more effective
[6]	Tian Bian et al.	Bi-Directional GCN	Rumor datasets	Combines top-down and bottom-up rumor propagation
[7]	Batool Lakzaei et al.	Literature Review	Multiple	Comprehensive review of GNN-based disinformation detection
[8]	Hua Shen et al.	BERTweet + Graph Attention	Twitter	Improved spammer detection with attention and social interaction modeling
[9]	Subhajeet Das et al.	1D CNN + GloVe	Twitter, Facebook, Instagram	Achieved 97%, 95%, 94% accuracy on respective platforms
[10]	Xing Su et al.	Hy-DeFake (HGNN)	4 datasets	Models high-order relations; links user credibility & news authority
[11]	Ling Sun et al.	HG-SL (Hypergraph + Self-Attention)	Real-world datasets	Detects early fake news using only user spreading behavior
[12]	Nikos Salamanos et al.	HyperGraphDis	Twitter (multiple domains)	High accuracy + efficiency; suitable for large/imbalanced datasets
[13]	V. Karuna et al.	GCN + CP Decomposition + Ensembles	Not specified	GCN reached 99% accuracy; ensembles aim for 100%
[14]	Alpana A. Borse et al.	HA2_HC_FNP_NN (Hierarchical + HGNN)	LIAR	Uses document/contextual vectors with attention + dynamic weighting
[15]	Alaa S. Mahdi, Narjis M. Shati	Review of GNN-based methods	Multiple	Summarized GNN techniques & datasets for researchers
[16]	Litian Zhang et al.	DGA-Fake (Generative Model)	3 datasets	Simulates propagation paths before news spreads; strong early detection

Table 1 provides a consolidated overview of recent advancements in fake news detection, focusing on studies that leverage machine learning, deep learning, and graph-based models. It encompasses 16 key research works that utilize diverse datasets such as UPFD, LIAR, FibVID, and various real-world Twitter datasets. The methods span from traditional LSTM and CNN architectures to more sophisticated frameworks like Graph Neural Networks (GNNs), Hypergraph Neural Networks (HGNNs), and attention-enhanced models. The contributions highlight innovations such as stance-aware propagation modeling, hierarchical attention mechanisms, and hypergraph-based relationship modeling. Notably, several studies demonstrate that incorporating relational and structural information from social media propagation networks—especially through GNNs and HGNNs—substantially improves detection accuracy, precision, and early detection capabilities. The table serves as a comparative guide for researchers and practitioners aiming to design effective and scalable solutions for combating misinformation in dynamic online environments.

Proposed Methodology

The proposed mechanism is being described in the figure 4.2 with the mention blocks in numbers. The first block shows types of data set and their associated features that is being given as a input for feature extraction through two types of associated model BERT and spaCy (in Block 2). Two steps 3 and 4 are the parallel steps that are engaged in extending news and creating the user engagement data sets through retweet and comment whereas the 4th one is engaged in user graph creation in tree structure respectively. The block 2 shares data to the PyG library and can work on node features like user profile features and user twitters to create user news graph network whereas after attention mechanism has been implemented over the user engagement graph then the preparation of fake news graph network was done. The proposed model creates a comparison between two floated directions of this work and compares the proposed model where attention mechanism was involved to optimize the UPFD fake news detection through attention mechanism. Attention mechanism already described in Figure 3.

Computation parameters and algorithm used for proposed discussed model is given as below. Apart from algorithm steps initial steps not discussed here as a part of reference from previous work in this field. Model configuration is also a major issue in implementation as every time result is not as per prediction due to real situation of environment.

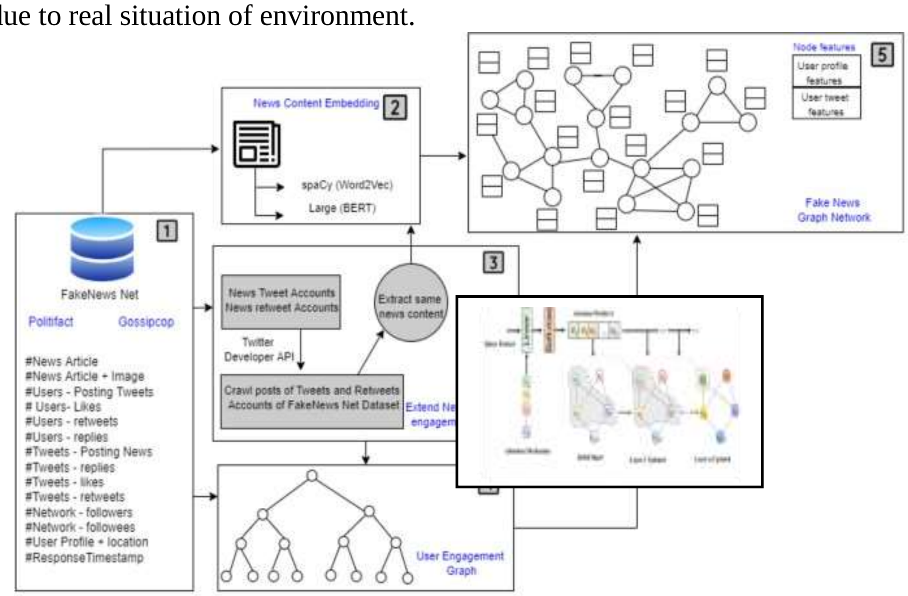


Fig.3. Proposed work block diagram

Implementation Results

Dataset named User Preference-aware Fake News Detection (UPFD) is a benchmark used in experiments of artificial intelligence and deep learning where fake & real news propagation on Twitter is being structure into tree-based graph. The benchmark has two variants, details shown in Table 2. To complete data acquisition step from twitter database, Twitter developer API and Tweepy helps to get user information. More details information for activities of a user is collected through crawling of history tweet publicly.

Table 2: UPFD statical data in graph structure

Dataset	Graphs (Fake)	Total Nodes	Total Edges	Avg. Nodes per Graph
Politifact (POL)	314 (157)	41,054	40,740	131
Gossipcop (GOS)	5464 (2732)	3,14,262	3,08,798	58

Statical data of table 2 is a collection from "FakeNewsNet" model implemented to generate node features of 20 million historical tweets from users in past years who participates in fake news sharing to other users. Pretrained model helps in features extraction from existing graph using BERT and spaCyword2vecin which 768 and 300 features were encoded using this pre-trained model as shown in table 3.

Table 3: Encoded feature and dimension

Feature	Dimension
User Profile	10D
User Comment	300 D
News Content	310D
Token Embedding extracted from BERT	768D

The implementation of BERT in 'FakeNewsNet' utilizes result tree structures as a social context graph, represented by three node feature vectors as shown in Figure 4.

Following feature extraction, the next phase of implementation involves feature selection and experimentation. In our proposed work, two major experimentations were completed to identify fake news on available tweet data structured in graph. To classify available tree-based data implementation of Experiment-1, collects sample graph in available label, apply different machine learning model and compared against proposed GNN model (with and without attention network) as shown in table 4 Experiment-2 focus on implementing Hyper Graph neural network implemented for classification which is an advance from of GNN customized with attention network. Experiment 1 conducted over ocean cloud platform and uses following configuration for three major model GCN, GNN and Sage having operational variation line continuous learning, forward network, Bi-direction, Attention network etc.

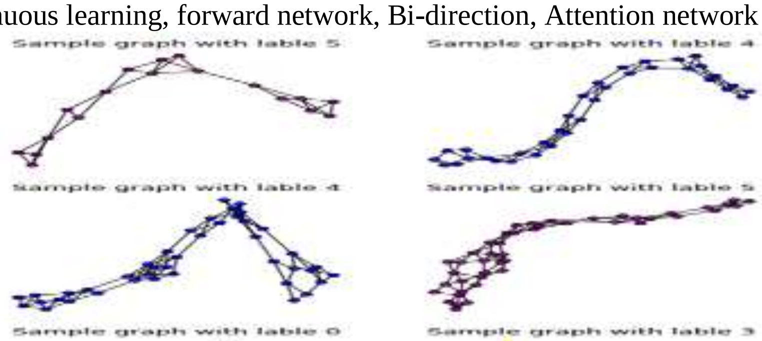


Fig.4. Social Context graph generated from Tweet information

Train and validation results on standard matrices Loss, Accuracy, Recall, and AUC was recorded for discussed model and proposed model (Experiment-1) compared on both category of dataset called Politifact, and Gossipcop. The model performance found a benchmarked against several state-of-the-art methods existing like graph neural network with continual learning, bi- directional graph convolutional network, graph attention network, graph convolutional network -SAGE, and graph convolutional network -forward network on direct extracted tweet dataset or UPFD dataset.

Table 4: Experimented model and Configuration used

Experimental Model	epoch	lr	nhid	Batch_size	dataset	seed	decay	No of classes
GNNCL	60	0.001	128	128	POL	777	0.001	2
GCNFN	100	0.001	128	128	POL	777	0.001	2
BIGFN	50	0.001	128	128	POL	777	0.001	2
GNNCL	60	0.001	128	128	GOS	777	0.001	2
GCNFN	100	0.001	128	128	GOS	777	0.001	2
BIGFN	50	0.001	128	128	GOS	777	0.001	2
UPFD-GNN/ GAT	50	0.001	128	128	GOS	777	0.001	2
UPFD-GCN	80	0.001	128	128	GOS	777	0.001	2
UPFD- SAGE	80	0.001	128	128	GOS	777	0.001	2
Proposed-1	80	0.001	128	128	POL/GOS	777	0.001	2

On run, result in reference platform numerical values under mentioned parameters are describing about implemented method performance. In training GNN displays approximate same result compare to proposed on Politifact type, whereas for Gossipcop significant differences. Proposed model on Gossipcop give 0.2723 (Training_loss), 0.9357 (Training_acc), 0.9951 (Training_recall), and 0.9988 (Training_AUC). Likewise against validation phase results also proposed model does well (on both Politifact and Gossipcop) compared to others. In validation phase Loss reaches to 0.4, accuracy reached to 0.96, Recall gets 0.555 and AUC reached to 0.9852. Pictorial Graphs for Training and Validation depicted through radar chart in figure 5 and 6. Analytical record of values after experiments and respective behaviors can be observed in figure 4 in pictorial form. After gathering varied experimental results output, we realized that our suggested system works good enough for acceptability. Out of other methods, GNNCL on Politifact and Gossipcop also works well. Proposed approach yields result accuracy of 0.9018 and 0.9784, F1_Macro 0.6922 and 0.9753, F1_mincro 0.7018 and 0.9654, precision 0.7477 and 0.9859, Recall 0.5646 and 0.9849, AUC 0.7457 and 0.9955 for Politifact and Gossipcop respectively. The results are found to not be good enough on Politifact due to lesser number of available charts obtained for target class identification as a consequence. SAGE is also among the good approaches seen in results on Politifact. But overall proposed method simulate graph well and get better with attention mechanism.

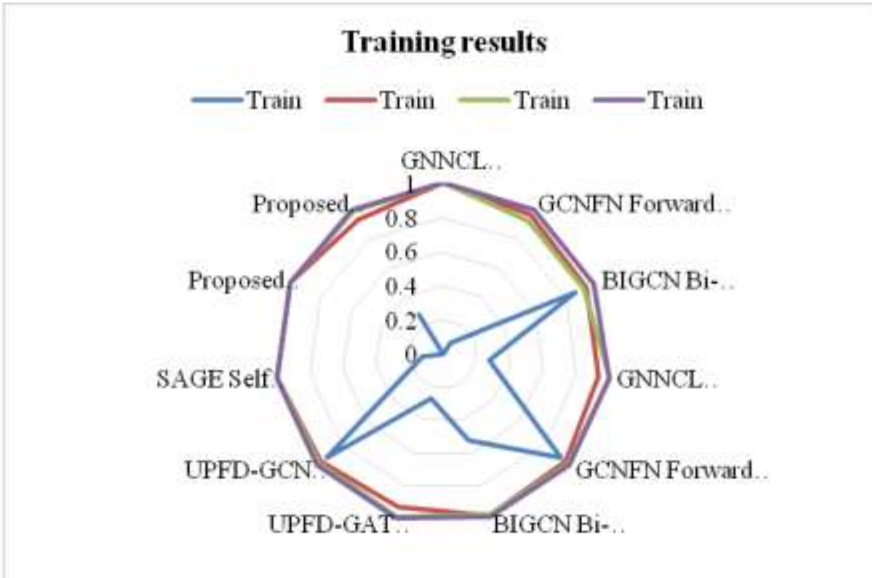


Fig.5. Radar graph of Training results achieved by different model

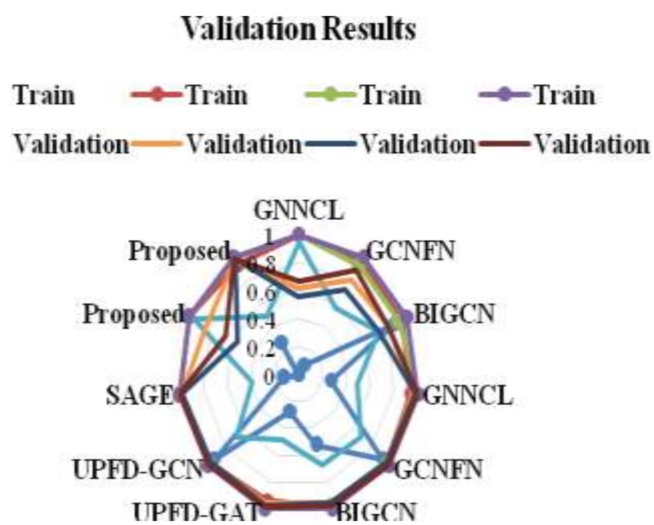


Fig.6. Radar graph for Validation Results achieved

The radar chart is appropriate for data that ought to be viewed as circular like intervals of time, data that shows direction, or graphing a collection of variables as a sequence of shapes that can assist in monitoring patterns and irregularities. Here in dataset have irregular pattern that is also present in results in available parameters. In provided charts all parameters are labeled with different color and data result pattern can clearly be seen. If results obtained have smaller variance in performed Experiment 1, then it can be easily concluded that slight improvement was found. Chaotic pattern of data sample indicates that no similarity found on respective parameter like in the Figure 5 on Training Loss parameter.

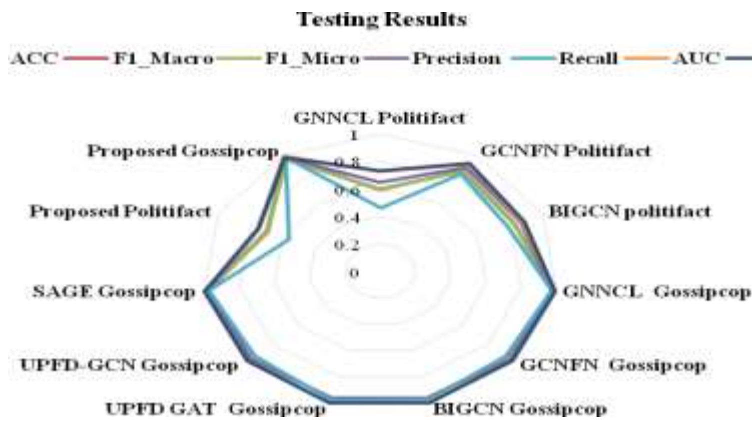


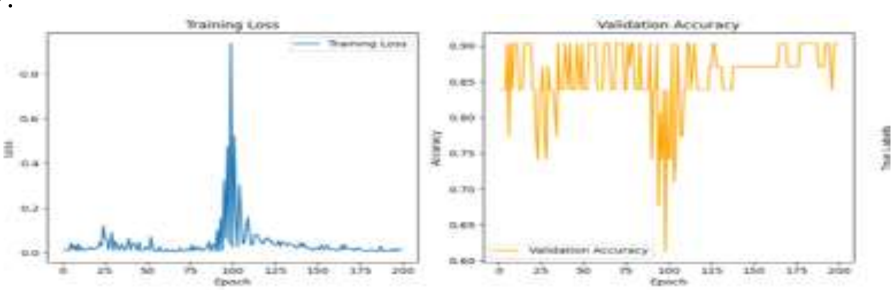
Fig.7. Testing Results in Radar Graph

Figure 7, represents the cumulative or extended collection of all valid data points for training and validation (as shown in figure 6) in the radar chart. It suggests that training loss and validation cannot be utilized as parameters to determine an effective technique. The simulation of data from the testing phase indicates that all parameters exhibit a smooth, circular sequencing without any disarray. This suggests that the engagement of all parameters is crucial for the evaluation of testing outcomes across all methodologies. Textual or non-textual features trained by proposed model-1 consider to identify impact on accuracy, precession, recall and F1 score with follower and non- follower users, timelines and combined. Both the chosen dataset opted consideration of impact with the help of support of tweet feature or profile feature in training Proposed-1 model.

Table 5: Performance comparison of models trained with/without non-textual features extracted from user timeline tweets

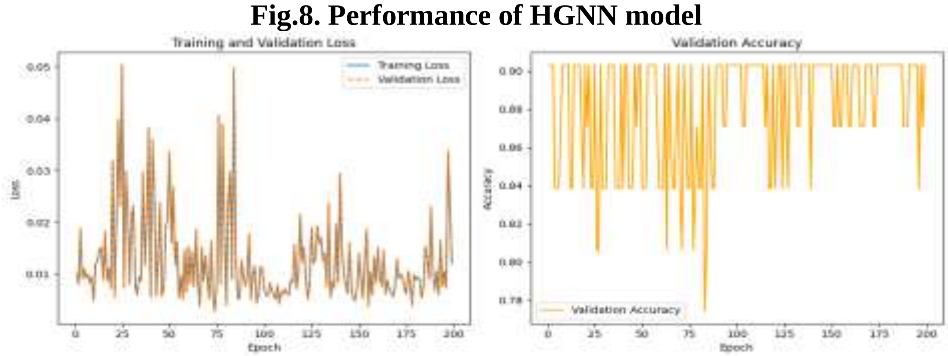
Dataset	Metric	User profile features only		Timeline tweets feature only		Combined	
		Without follower/ Following	With follower/ Following	Without follower/ Following	With follower/ Following	Without follower/ Following	With follower/ Following
PolitiFact	Acc	0.812	0.807	0.698	0.696	0.795	0.807
	Pre	0.811	0.808	0.702	0.698	0.796	0.809
	Rec	0.811	0.803	0.609	0.609	0.796	0.805
	F1	0.809	0.803	0.607	0.605	0.795	0.805
GossipCop	Acc	0.849	0.846	0.856	0.856	0.852	0.844
	Pre	0.827	0.825	0.837	0.835	0.833	0.824
	Rec	0.835	0.836	0.854	0.848	0.842	0.832
	F1	0.828	0.827	0.842	0.838	0.834	0.826

Experiment-2 was conducted to check impact of Hypergraph neural network on UPFD dataset which work on high order relation in users, their post and activities. Collected features metadata prepared a hypergraph incidence matrix and used for classification model HGNN for learning. Subsequently, the HGNN architecture is composed of several layers: an embedding layer that learns low-dimensional node representations; an attention mechanism that gives hyperedges priority; and a message-passing layer that updates node features by aggregating information from neighbor nodes connected by hyperedges. The network is trained using the Adam optimizer, and binary cross-entropy is used as the loss function. To ascertain if a news story is genuine or counterfeit, the final classification layer employs a soft-max function. To evaluate the effectiveness of the HGNN, standard classification measures like accuracy, precision, recall, and F1-score are employed. Accuracy evaluates the model's overall right predictions, whereas precision and recall measure the model's ability to correctly differentiate fake news from false positives and false negatives. The F1-score's ability to balance precision and recall is a key characteristic of imbalanced datasets like UPFD, where the percentage of fake news instances relative to actual news instances is typically lower. Furthermore, the model's capacity to differentiate between the two classes across a number of choice criteria is assessed using the area under the ROC curve (AUC-ROC). Figure 8 displays the training and validation accuracy results of the HGNN with attention network implementation, along with a confusion matrix as shown in figure 8. Training loss and validation accuracy for each epoch up to 200 counts are displayed in this figure 8. These graphs indicate floating in training loss and validation accuracy in first epochs, while iterative epochs exhibit a discreated loss. Accuracy reached 94.32% on the 200th epoch, and training loss began to decrease after 100 epochs to the relative ideal value of 0.0157.



(a) Training Loss (b) Validation Accuracy

Fig.8. Performance of HGNN model



(a) Training and validation Loss (b) Validation accuracy

Fig.9. Performance of HGNN model with attention mechanism

Following model training, the same set of 200 epochs was used for testing to confirm the results. The trained proposed model's testing results for validation of model accuracy and validation loss are displayed in Figure 9. The impact of unbalanced test data is being reported by training and validation losses, which now exhibit distinct patterns and are highly unpredictable throughout epochs of repetition. Due to an efficient optimizer, a very slight difference between training and validation loss was recorded this time. The HGNN's attention mechanism, which is chosen over weight adjustment during the first training phase, is the reason for this efficient optimization. The optimum training characteristics for both fictitious and real data classes are mapped by this HGNN weight adjustment.

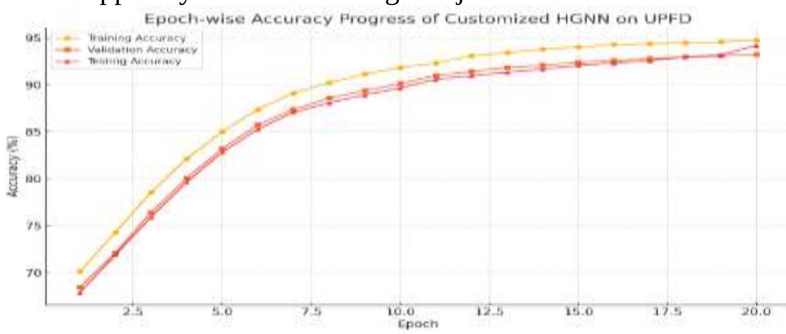


Fig.10. Experiment-2, epoch's wise model performance

The above figure 10 shows model performance seen at time of evaluation of Attention-Based Hypergraph Neural Network (HGNN) trained on the UPFD dataset for fake news detection shows the epoch-wise evolution of training, validation, and testing accuracy in the graph. All three accuracy curves exhibit a steady rising trend over the course of 20 epochs, suggesting that the model is learning and generalizing well. Training accuracy begins at 70.12% and gradually rises to 94.75% at the end of the epoch. Accuracy levels for testing and validation come in close succession, starting at 68.45% and 67.88%, respectively, and eventually surpassing 93%. As training accuracy increases along with validation and testing results, the simultaneous improvement across all datasets indicates that the model is not overfitting.

Comparative Results

Comparative analysis of both implemented proposed methods are compared against previous model and tried to find the impact of attention mechanism on training and testing of in proposed work. Table 6 shows the results of all implemented models within the proposed work and comparative analysis on standard matrices. As a result, we found that Experiment-2 Proposed attention based HGNN model outperforms on the given environment to find the fake news on UPFD dataset.

Table 6: Performance comparison of two implemented model

Implemented Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)
Proposed Attention-Based HGNN	**94.21**	**93.85**	**94.5**	**94.17**	**96.1**
HGNN	**90.1**	**89**	**90.5**	**91.1**	**90.3**
Attention based GNN	**90.18**	**88.9**	**90.6**	**92.05**	**91.1**
GNN	**89.79**	**88.7**	**90.12**	**92.01**	**91**
GCN (Graph Convolutional Network)	89.32	88.95	89.4	89.17	92.3
GAT (Graph Attention Network)	90.85	90.5	90.2	90.35	93.1
Heterogeneous Graph Neural Network (HetGNN)	91.23	91.1	90.8	90.95	94

Stating a more elaborate analysis of the results GNN is also a good model which has been implemented in the Experiment 1 and propose a attention based model in our work while previous 1traditional methods like GCN, GAR HetGNN, DGCNN, BiLSTM, CNN-LSTM SAGE, RCN and HGT is not as per marks to compete proposed models. Understanding the need of graph-based text analysis is now seen very effective by founded shown results. Opposite to this RoBERTa also performs very well and outstand result seen in comparison to Experiment-1, but in Experiment-2 which is based on HGNN (attention based) perform well to showcase active process of attention network and their effectiveness in training classifier model. Performance comparison bar graph shown in figure 11, that show all metric performance in different colour in close bar for all respective models.

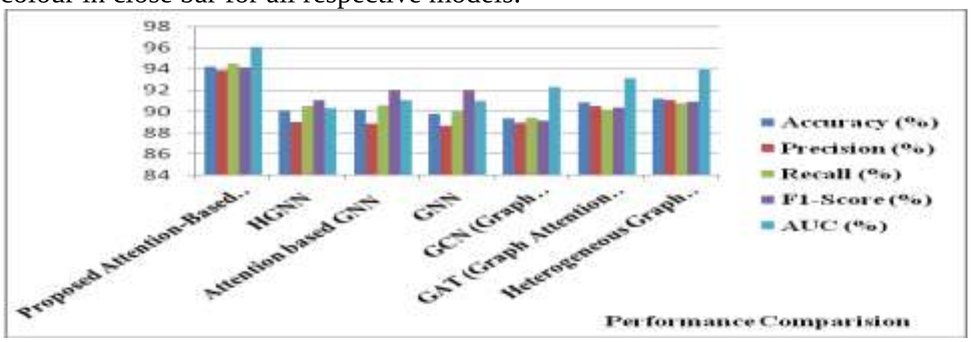


Fig.11. Performance comparison of proposed experiments

Now the trained model is being tested over the real tweet done over the Twitter platform related to politics health sports economy and technologies. For a single type of text with these keywords in different news was tested in different samples 1 to 20 and their prediction has been checked using a real and fake scores generated by proposed model. Figure 11 shows prediction and their results in the form of Fake and real score. Shown results shows that model have a good confidence of predicting class of news in "Fake" or "Real" and confidence parameters seen is >= 85 % of confidence of model shows fine and accurate results for target class. Tweepy API helps in collecting UK news text sample in given related field and 20 samples was tested to check accuracy of news text classification and found accurate prediction on given distribution sample of tweet data, given in figure 11.

Fig.12. Distribution of fake and real news in 20 sample data for prediction

Conclusion

This work underscores the effectiveness of incorporating advanced neural architectures—Graph Neural Networks (GNNs) with attention mechanisms and Hypergraph Neural Networks (HGNNs)—for fake news detection on complex datasets like UPFD. The attention-augmented GNN demonstrated significant improvements in classification metrics, including accuracy, precision, recall, and F1-score, by dynamically weighing the contextual importance of surrounding nodes. This enhancement allowed the model to better capture subtle relational signals and contextual dependencies crucial for misinformation detection. Furthermore, attention mechanisms helped overcome limitations of traditional and deep learning models by improving feature representation and enabling the model to focus on semantically relevant data. However, challenges such as overfitting due to excessive node seeding and extended training epochs (e.g., beyond 120) were observed, especially in large-scale datasets like Gossipcop, suggesting the need for model regularization and efficient node preparation strategies. On the other hand, HGNNs demonstrated superior capability in modeling higher-order interactions among users, posts, and news articles. The use of hyperedges allowed for more nuanced and comprehensive feature extraction that surpassed the capabilities of conventional GNNs and machine learning models such as logistic regression and random forests. The integration of attention mechanisms within HGNNs further boosted performance by emphasizing the most influential relationships in the hypergraph. Together, these approaches affirm that both local and high-order relational structures are pivotal in fake news detection. Future research should focus on optimizing feature mapping, profile modeling, scalability, and transfer learning to enhance performance and robustness across various datasets and social platforms.

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