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Dynamic Graph Attention Network with Sentiment Analysis for Fake News Detection in Social Networks

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ABSTRACT

Detecting fake news on social media platforms remains a significant challenge due to the dynamic nature of these networks, evolving user-news relationships, the difficulty in distinguishing real from fake information, and the use of advanced generative models to create fake content. In this study, we propose a novel approach, the Dynamic Graph Attention Network (DynGAT), for effective fake news detection. The DynGAT model utilizes the dynamic graph structure of social networks to capture the evolving interactions between users and news sources. It includes a graph construction module that updates the graph based on temporal data and a graph attention module that assigns importance to nodes and edges within the graph. The model applies attention mechanisms to prioritize critical interactions and uses deep learning techniques to classify news articles as real or fake. Experimental results on the TweepFake dataset (20,712 samples) show that DynGAT achieves 95% accuracy, outperforming existing methods such as Static GNN (87%), Transformer-based models (91%), and Hybrid models (89%). The model also demonstrates improvements in precision, recall, and F1 score. This work contributes to the ongoing efforts to combat misinformation and promote reliable information on social media platforms.

Keywords— Fake news detection, social networks, dynamic graphs, temporal information, Sentiment Analysis.

1. Introduction

The rise of online social media platforms has revolutionized the way we connect with others and consume news. It has provided us with unprecedented opportunities to exchange opinions and access information quickly. However, this convenience also comes with challenges, particularly in the form of fake news. Fake news refers to false or misleading information presented as factual news [1]. The nature of online social media platforms, with their lack of effective regulation and fact-checking measures, makes them fertile ground for the spread of fake news. Unlike traditional news media, which often follow rigorous research and fact-checking processes to ensure accuracy, online platforms allow anyone to create and publish content without such scrutiny [2]. The motivations behind the creation and dissemination of fake news can vary. Some individuals or groups may aim to influence public opinion on certain issues, while others might be driven by the potential for financial gain. Regardless of the motives, the low cost and ease of spreading fake news online have made social media platforms the primary channels for the propagation of such misinformation[3]. To address this issue, there have been efforts to develop tools and strategies for detecting and combating fake news. Fact-checking organizations and algorithms have been implemented to verify the accuracy of news articles and flag potential falsehoods. Additionally, platforms like Facebook and Twitter have introduced measures to limit the reach and visibility of fake news content [4, 5]. The battle against fake news is an ongoing challenge, as new tactics and technologies are constantly emerging. Individuals need to be critical consumers of news, fact-check information before sharing, and rely on trusted sources. Furthermore, continued efforts from both platforms and users are necessary to promote accurate and reliable information in the online social media landscape [6].

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The World Economic Forum has indeed recognized fake news as a major threat to society [7]. Human beings are not always adept at distinguishing between real and fake news. This is why there is a growing need for automated solutions to detect and combat fake news on social media platforms. Manual fact-checking by a small group of credible fact-checkers is time-consuming and cannot keep up with the volume of emerging fake news [8, 9]. Computational fake news detection has emerged as a potential solution to this problem [7]. By leveraging artificial intelligence and machine learning techniques, researchers and technologists are developing algorithms that can automatically identify and flag fake news content. These algorithms analyze various aspects of news articles, such as language patterns, sources, and social media engagement, to determine their credibility [10, 11]. However, detecting fake news computationally is a complex task. It requires the development of sophisticated models and the continuous training of algorithms to adapt to evolving tactics employed by creators of fake news. Researchers are also exploring the use of collaborative filtering, network analysis, and other techniques to improve the accuracy of fake news detection [11-13]. Efforts in computational fake news detection are crucial for combating the spread of misinformation on social media platforms. By automating the process, it becomes possible to scale up the detection and response to fake news, ultimately helping to protect public opinion and maintain a healthy information ecosystem. By analyzing the digital footprints left by users when sharing and discussing fake news, researchers can develop effective detection and intervention techniques to assess the veracity of such news and minimize their impact. Traditionally, machine learning algorithms have been used in fake news detection by manually designing engineering features that capture relevant information from news articles and social media interactions. However, this approach is time-consuming, lacks generalizability, and can result in biased features.

In recent years, deep learning algorithms have gained popularity and have been successfully applied to various tasks, including sentiment analysis, fake news detection, and question-answering [14-18]. These algorithms can automatically capture complex patterns from raw data, eliminating the need for extensive feature engineering. Deep learning-based fake news detection methods have shown promise in mitigating the limitations of traditional machine learning approaches. These methods use neural networks to learn representations directly from the raw text of news articles and social media posts. By training on large datasets, deep learning models can identify subtle patterns and features that are indicative of fake news. The advantage of deep learning-based approaches lies in their ability to adapt and learn from diverse and evolving data sources. However, it is important to note that the effectiveness of deep learning models relies heavily on the quality and diversity of the training data. Ensuring the availability of comprehensive and reliable datasets is crucial for the development of accurate and robust fake news detection systems. So deep learning-based fake news detection methods offer a promising avenue for addressing the challenges posed by fake news on social media platforms. By leveraging the power of deep learning algorithms, researchers can develop more effective and scalable solutions to combat the spread of misinformation [5, 10, 18].

Traditional approaches to fake news detection have primarily focused on analyzing the content of news articles. However, these methods often overlook the dynamic nature of news propagation and fail to capture the evolving patterns of information diffusion [19]. To address this limitation, we propose a novel model called the Dynamic Graph Attention Network (DynGAT) for fake news detection. The DynGAT model leverages the dynamic graph structure of social networks to enable accurate and timely detection of fake news. By considering the temporal dynamics of news propagation, the model captures the evolving relationships between users and news sources, allowing for a more comprehensive understanding of the spread of information. The key components of the DynGAT model include a graph construction module and a graph attention module. The graph construction module dynamically updates the graph representation based on temporal information, considering user engagement patterns and news source credibility. This ensures that the model captures the latest information and adapts to changes in the network structure.

The graph attention module models the importance of nodes and edges in the dynamic graph. By incorporating attention mechanisms, the model focuses on crucial interactions between users and news sources, prioritizing and analyzing important information for fake news detection. This attention mechanism allows the model to effectively capture the most relevant features and make accurate predictions about the veracity of news articles.

To encode and classify news articles, the DynGAT model utilizes deep learning techniques, including recurrent neural networks (RNNs), convolutional neural networks (CNNs), and attention mechanisms. By considering the temporal dynamics and leveraging attention mechanisms, the model captures the semantic information and contextual features of news articles, enhancing the accuracy of fake news detection.

In this study, we aim to address the limitations of static graph-based fake news detection models by proposing the DynGAT model. We conduct extensive experiments on real-world datasets to evaluate the performance of the model and compare it with existing approaches. The results demonstrate the effectiveness of the DynGAT model in accurately and timely detecting fake news. This study contributes to the field of fake news detection by leveraging the dynamic graph structure of social networks. The proposed DynGAT model offers a novel approach that captures the evolving patterns of news propagation and enhances the accuracy of fake news detection. With the increasing prevalence of fake news, our model provides a valuable tool to combat the spread of misinformation and preserve the integrity of information in the digital era. Unlike traditional static graph-based fake news detection methods, which often fail to account for the evolving patterns of information diffusion, our proposed approach introduces several key innovations. First, we leverage a dynamic graph construction mechanism that evolves with temporal user interactions and news credibility. This dynamic representation allows the model to adapt in real time to the rapidly changing nature of social media environments.

Second, the use of a Graph Attention Network (GAT) enables the model to prioritize critical interactions between users and news articles. By assigning varying importance to nodes and edges in the dynamic graph, the model focuses on the most relevant features for accurate fake news detection. Additionally, we incorporate sentiment analysis into the detection process, capturing the emotional tone often associated with misleading or fabricated content.

Finally, our hybrid approach combines graph-based features with deep learning techniques for text-based analysis, such as RNNs and CNNs, enhancing the model's ability to analyze both the content and propagation dynamics of fake news. These contributions collectively enable our model to outperform existing methods, offering a scalable and effective solution to the challenges posed by fake news in social networks.

2. **Related Work**

Fake news has emerged as a significant societal challenge in recent years, as the rapid spread of misinformation through social media platforms has the potential to manipulate public opinion, influence elections, and undermine trust in reliable sources of information. Detecting and combating fake news has thus become a critical area of research [20-23]. Traditional approaches to fake news detection primarily focused on analyzing the content of news articles, utilizing linguistic features, metadata, and fact-checking. While these methods demonstrated initial promise, they often struggled to keep pace with the evolving techniques used by fake news creators and failed to capture the dynamic nature of news propagation [21].

To address these challenges, researchers have explored graph-based approaches, which represent the complex relationships between users, news sources, and information dissemination. By modeling the graph structure, these approaches aim to capture the dynamics of information diffusion and identify patterns associated with fake news propagation [24-29]. One common approach has been to construct static graph representations of social networks, analyzing connectivity patterns among users and news sources using features like centrality measures, community detection, and graph clustering [30, 31]. However, static methods often overlook temporal dynamics such as user engagement, temporal patterns, and source credibility, which can result in untimely and inaccurate detection of fake news [32].

Dynamic graph-based models have emerged as a solution to this limitation. These methods capture the evolving relationships between users and news sources over time, allowing for more accurate and timely detection. By integrating temporal information and attention mechanisms, dynamic models prioritize critical interactions and reflect the dynamic nature of news propagation. For instance, Dynamic-GCN [32] and TGNF [26] use temporal graph networks to model changes in user behavior, while SEAGEN [33] highlights key engagement moments by modeling self-exciting phenomena.

In addition to dynamic graph-based methods, knowledge-driven techniques have enriched graph representations by incorporating external sources like Wikipedia to identify inconsistencies between news content and verified information. Models like KMGCN [34] and CompareNet [35] improved robustness by leveraging external knowledge graphs, but their reliance on external databases posed scalability and real-time applicability challenges. Another significant development has been propagation-based methods, which model the dissemination process of news in social networks. Bi-GCN [36], for example, constructed bi-directional graphs to capture both top-down and bottom-up dynamics, while DUCK [37] integrated structural and temporal information into propagation graphs to enhance detection accuracy. Despite their utility, many propagation-based methods still treated graphs as static, limiting their adaptability to evolving user interactions.

Hybrid models combining graph-based and text-based techniques have also gained attention. RDLNP [38] integrated graph convolutional networks (GCNs) with sequence models like LSTMs to jointly analyze structural and textual features, while Sure-Fact [39] employed reinforcement learning to filter irrelevant subgraphs, improving graph representation accuracy. These models demonstrated the potential of combining multiple modalities but required significant computational resources for large-scale networks.

Graph Attention Networks (GATs) introduced another powerful approach by prioritizing key nodes and edges through attention mechanisms. Models like KGAT [40] and DUCK [37] enhanced interpretability and classification performance by applying attention layers to highlight influential interactions in propagation graphs. However, their reliance on static graphs limited their ability to account for temporal dynamics. Recent advancements in integrating temporal information and attention mechanisms, such as Dynamic-GNN and SEAGEN, have further emphasized the importance of capturing dynamic interactions to improve fake news detection.

The EGNN (Ensemble Graph Neural Network) model [41] is another significant advancement that combines multiple GNNs, including standard GNNs, GATs, and Bi-GCNs, to effectively model user engagement patterns and social context. Additionally, EGNN incorporates text embeddings extracted using BERT and Spacy, along with ensemble learning techniques like Majority Voting and Stacking, to enhance detection accuracy even with limited labeled data. EGNN also addresses class imbalance using focal loss, further demonstrating its robustness and scalability for fake news detection tasks.

The DynGAT model proposed in this study builds on these advancements by introducing a dynamic graph attention mechanism that integrates temporal dependencies and enriched node features. Unlike static approaches, DynGAT dynamically updates the graph structure to reflect user interactions over time, capturing the evolving patterns of news propagation. The model also employs hybrid learning techniques, combining CNNs, RNNs, and graph embeddings to jointly exploit textual and structural information.

Through extensive experiments on real-world datasets, the DynGAT model demonstrates its effectiveness in accurately detecting fake news and providing timely results. By addressing critical gaps in scalability and interpretability, DynGAT outperforms existing methods and positions itself as a benchmark in the field of dynamic graph-based fake news detection. This study contributes to the growing body of research focused on combating misinformation in the digital age, highlighting the need for innovative approaches to adapt to the ever-changing nature of fake news propagation.

3. Node Feature Representation

The feature vector for each node ***i*** contains essential information that helps distinguish between real and fake news content. These features play a key role in the DynGAT model, enabling it to effectively analyze and classify nodes based on their content and characteristics. To avoid ambiguity in the notation, we define the following:

- F_i: This represents the **global feature vector** of node ***i***, capturing the overall characteristics of the node. For example, for a news node, this may include properties such as credibility (real or fake), while for a user node, it may include profile-related attributes like account type.
- $f_i(t)$: This denotes the **local feature vector** of node ***i*** at time ***t***, reflecting the evolving interactions and dynamics as the graph develops over time. The features of the node may change at different time steps due to new interactions or updates.
- $h_i(t)$: This represents the **hidden feature vector** of node ***i*** at time ***t***, processed through the **graph attention mechanism**. The attention layers modify the feature vector based on interactions with other nodes, allowing the model to focus on the most relevant features.

These feature vectors are critical for the DynGAT model to analyze the content and interactions within the dynamic graph and make accurate predictions regarding the authenticity of news content. The definitions and their usage are further elaborated in Section 5, where the model's methodology is explained.

4. Problem Formulation

In this study, we aim to detect fake news in a dynamic news propagation network using the proposed DynGAT model. The network is represented as a dynamic graph, denoted as $G = (V, E, T)$, where V represents the set of nodes (news articles or tweets), E represents the set of edges (interactions between nodes), and T represents the set of timestamps indicating the temporal order of interactions.

Each node in the dynamic graph represents a news article or tweet and is associated with a feature representation, denoted as F. The feature representation captures important characteristics of the news article or tweet, including textual content, social context, temporal dynamics, and source credibility. Equ (1) provides the node feature representation:

$$F = \{f_1, f_2, \dots, f_n\} \quad (1)$$

- \- F Node feature representation capturing characteristics of news articles or tweets

- - f_i: Feature vector representing the attributes of node i
- - n: Total number of nodes in the dynamic graph

The feature vector f_i, for each node i contains information that helps in distinguishing between real and fake news content. These features are essential for the DynGAT model to effectively analyze and classify nodes based on their content and characteristics. By representing the node features in a structured and organized manner, the DynGAT model can leverage this information to make accurate predictions regarding the authenticity of news articles or tweets in the dynamic news propagation network.

The edges in the dynamic graph signify interactions between nodes at different timestamps. Edge interactions *E = (i, j, t)* indicates that node *(i)* responds to node *(j)* at timestamp *(t)*. These interactions reflect the flow of information and influence between nodes in the network. The problem at hand is to develop the DynGAT model to effectively detect fake news in this dynamic news propagation network. The model should be able to leverage the dynamic graph structure, the feature representations of the nodes, and the temporal dynamics of interactions to accurately classify nodes as real or fake at different timestamps. Equ (2) shows the prediction function:

$$y_i = f_{\{\text{text}\{\text{DynGAT}\}\}(}F_i, E_i) \tag{2}$$

where (y_i) is the predicted label for node *(i)* based on its features (F_i) and interactions (E_i). The DynGAT model processes the node features and interactions to predict the likelihood of fake news for node *(i)*.

By formulating the problem in this way, we can focus on developing a model that can capture the evolving nature of fake news in the dynamic network and make accurate predictions at different points in time. The DynGAT model combines graph attention mechanisms with deep learning techniques to effectively analyze the dynamic graph and detect fake news.

5. **Methodology**

In this study, we introduce the DynGAT model as a novel approach for the accurate and timely detection of fake news. The key innovation of our method lies in its ability to dynamically capture the evolving structure of social networks and seamlessly integrate this information into the classification process. Unlike conventional approaches that depend on static graph representations, our methodology leverages a dynamic graph construction module, which models temporal interactions and user behavior evolution while enriching the graph with node features extracted from textual data (e.g., TF-IDF representations) and edge attributes that capture user interaction patterns. Additionally, we enhance the standard Graph Attention Network by incorporating temporal dependencies and refining its attention mechanisms to better highlight the propagation dynamics characteristic of fake news dissemination. To further improve classification performance, we employ advanced deep learning techniques, utilizing ensemble models that combine RNNs, CNNs, and attention mechanisms to encode textual content. These textual representations are then fused with graph embeddings to effectively exploit both structural and semantic information. This synergy between dynamic graph representation, advanced attention mechanisms, and hybrid feature integration represents the core contribution of our work, setting a new benchmark for fake news detection (Figure 1).

5.1. Dataset Description

In this study, we utilized the TweepFake[1] [2]-Twitter Deep Fake Text Dataset, a comprehensive and balanced dataset specifically designed for detecting deep fake texts on social media platforms. This dataset comprises 20,712 samples, equally distributed between two categories: Real (Human-written) and Fake (Machine-generated). The fake texts were generated using advanced language models such as GPT-2, RNN, and other generative techniques. This dataset is a valuable resource for researching deep fake text detection in real-world social media settings. It provides realistic and short texts like actual tweets, making it well-suited for evaluating the performance of detection models. Furthermore, the dataset's balanced nature ensures reliable and unbiased training and testing of models. The TweepFake dataset is structured with each sample containing attributes such as user_id, status_id (tweet ID), screen_name, account.type, class_type (label), and the tweet text. It is perfectly balanced, featuring 10,358 human-written texts labeled as 0 and 10,354 machine-generated texts labeled as 1. The fake texts are further categorized based on their generation method, including GPT-2, RNN, and other less-specified techniques. The dataset is divided into three subsets: a training set comprising 90% of the total data (10,358 real and 10,354 fake samples), a validation set consisting of 10% of the training data (1,150 real and 1,152 fake

[1] https://www.kaggle.com/datasets/mtesconi/twitter-deep-fake-text

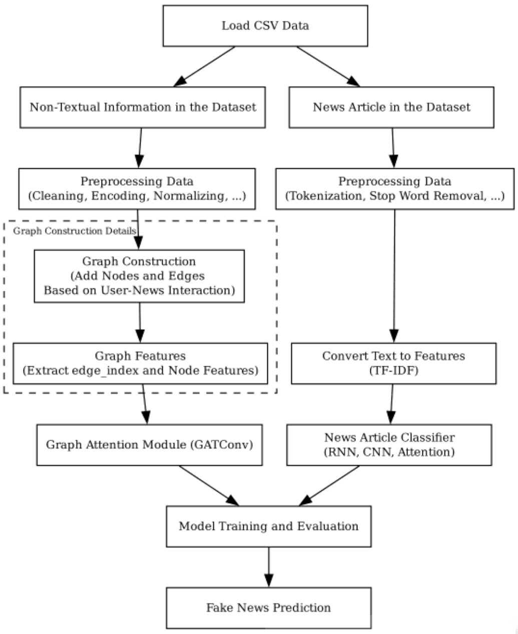

Figure. 1. DynGAT Model Pipeline

samples), and a test set representing 10% of the dataset (1,278 real and 1,280 fake samples).

5.2. **Graph Construction Module**

The graph construction module dynamically creates and updates a graph representation of social networks by accounting for both **user engagement patterns** and **news source credibility**. Nodes in the graph represent users and news articles, while edges represent interactions between them, such as sharing or commenting. The graph evolves over time as more user interactions are recorded, capturing the evolving nature of news dissemination on social media. The construction process includes the following steps:

- Node creation: User nodes are initialized with attributes such as screen_name and account_type, while news nodes include properties like text_length and credibility (real or fake).
- Edge creation: Interactions between users and news articles are represented as edges, each weighted to reflect interaction strength.
- Feature extraction: Node features are derived based on their type. For user nodes, features include the degree of interaction and account type (e.g., human or bot). For news nodes, features include text length and credibility.

Figure 2 illustrates a segment of the constructed graph, where red nodes represent users, green nodes represent news articles, and edges denote interactions between them (e.g., shares, comments, or likes). This Figure highlights how user-based and content-based

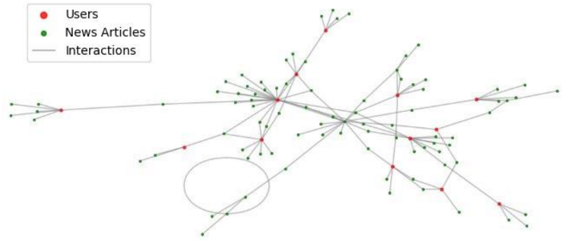

Figure. 2. Visualization of the Social Network Graph.

features are integrated into the graph structure, ensuring a holistic approach to fake news detection.

The process begins by gathering real-time interaction data, including:

- User-to-news interactions (e.g., shares, comments).
- Temporal information (timestamps of interactions).
- News credibility is based on predefined trust scores.

The **dynamic nature** of this graph allows the system to continuously update its understanding of how information flows across the network. For each time step t, the graph structure $G_t = (V_t, E_t)$ is updated with new interactions. This evolving graph reflects the temporal changes in relationships and interactions in the network, crucial for detecting fake news as it spreads (Table 1).

5.3. **Graph Attention Module**

Attention is a mechanism inspired by human cognitive processes, enabling systems to selectively focus on the most relevant information while filtering out less critical details. This selective focus mirrors the way humans allocate attention to important stimuli in a complex environment. In machine learning, attention mechanisms dynamically assign weights to different parts of the input data, highlighting the features or interactions that are most relevant to the specific task. By doing so, they enhance the model's ability to capture subtle patterns and relationships within the data.

Building on this foundation, the **Graph Attention Module** leverages attention mechanisms to evaluate the importance of nodes and edges in a dynamic graph. In a network with thousands of nodes and edges, interactions vary in significance, and not all contribute equally to the detection of fake news. This module dynamically assigns weights to these nodes and edges, allowing the model to prioritize the most critical interactions—such as those involving highly active users or suspicious content sources—that are more likely to influence the spread of misinformation.

Table 1. Graph Construction Features

Feature Type	*Description*	*Examples*
User Features	Profile information, interaction history	User credibility score
News Article Features	Linguistic patterns, source credibility, topical alignment	Trustworthiness score
Interaction Features	Number of shares, comments, likes, time intervals between interactions	Edge weights between nodes

The attention score α_{ij} between nodes i and j is calculated using a function Equ (3) that captures the relevance of the nodes' features:

$$\alpha_{ij} = \text{softmax}\left(\text{LeakyReLU}\left(\mathbf{a}^T[\mathbf{Wh}_i \parallel \mathbf{Wh}_j]\right)\right) \quad (3)$$

where:

- $\mathbf{W}$ is the weight matrix.
- $\mathbf{h}_i$ and $\mathbf{h}_j$ are the feature vectors of nodes i and j.
- $\mathbf{a}^T$ is the learnable weight vector.

By applying attention scores, the model emphasizes critical interactions, such as those involving users with high engagement or articles from highly suspicious sources Figure 3, illustrates the Graph Attention Module, highlighting the interactions between users and articles. The edges represent attention scores that reflect the strength of these connections, with higher scores indicating greater relevance.

5.4. News Article Encoding and Classification

The task of encoding and classifying news articles as real or fake is achieved through a hybrid approach involving deep learning models. Recurrent Neural Networks (RNNs) are employed to capture the temporal relationships within the text, enabling the model to understand the sequence and context of words. At the same time, Convolutional Neural Networks (CNNs) are used to extract local features, identifying important textual patterns such as key phrases or sentence structures. To enhance accuracy, an attention mechanism is integrated into the model, allowing it to focus on the most critical parts of the article, particularly sensational or misleading keywords that are often characteristic of fake news (See Figure 4).

5.5. Training and Evaluation

The DynGAT model is designed to identify and classify news articles as either real or fake by leveraging large-scale, labeled datasets that include a diverse range of real and fake news sources. During the training phase, the model employs advanced

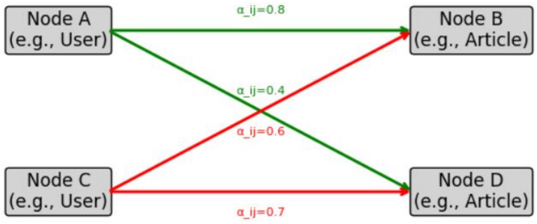

Figure. 3. Graph Attention Module

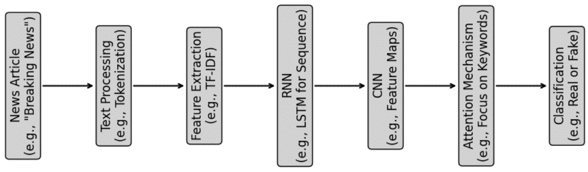

Figure. 4. News Article Classification Pipeline

optimization techniques such as backpropagation and gradient descent to minimize classification errors. Specifically, the model fine-tunes its parameters to reduce the classification loss, which helps in improving the accuracy of predictions.

To gauge the model's performance, a variety of evaluation metrics are utilized (Table 2).

- ***Accuracy:*** This metric calculates the overall percentage of news articles that the model correctly classifies as real or fake. It provides a general measure of the model's performance across all categories.
- ***Precision:*** Precision focuses on the quality of the model's predictions for fake news articles. It assesses the percentage of articles flagged as fake that are indeed fake, thereby evaluating the model's ability to avoid false positives.
- ***Recall***: Recall measures the model's effectiveness in detecting fake news articles. It determines the proportion of actual fake news articles that the model successfully identifies, reflecting its capability to minimize false negatives.
- ***F1 Score:*** The F1 Score combines both precision and recall into a single metric, offering a balanced view of the model's performance. It is particularly useful in scenarios where there is a trade-off between precision and recall, and it provides a harmonic meaning that emphasizes both metrics equally.

6. Results

The performance of the DynGAT model has been extensively evaluated and compared against several baseline models, demonstrating its superior capabilities in fake news detection. The DynGAT model’s strength lies in its integration of dynamic graph structures and attention mechanisms, which

Table 2. Evaluation Metrics for Fake News Detection

Metric	Description	Formula
Accuracy	Percentage of correctly classified articles	$\frac{TP + TN}{TP + TN + FP + FN}$
Precision	Proportion of true fake news among predicted fake news	$\frac{TP}{TP + FP}$
Recall	Proportion of fake news detected	$\frac{TP}{TP + FN}$
F1 Score	Harmonic mean of precision and recall	$2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$

enable it to adapt to evolving information flow and detect subtle patterns indicative of fake news with high accuracy.

Table 3 presents a comprehensive comparison of DynGAT with a range of baseline models, including static Graph Neural Networks (GNN), traditional machine learning (ML) models, as well as more recent approaches like Transformer-based models and Hybrid models.

- **DynGAT** outperforms all listed models with an accuracy of 95%, precision of 94%, recall of 93%, and an F1 Score of 93.5%. This demonstrates its exceptional ability to accurately detect fake news and adapt to changes in information flow.
- **Static GNN** shows strong performance with an accuracy of 87%, precision of 85%, recall of 84%, and an F1 Score of 84.5%. However, it lacks the dynamic adaptability of DynGAT.
- **Traditional ML** models, specifically the Decision Tree classifier used in this study, while foundational, exhibit lower performance with an accuracy of 82%, precision of 80%, recall of 78%, and an F1 Score of 79%. This highlights the advancements in more recent methodologies over traditional approaches.
- **Transformer-based** models provide robust performance with an accuracy of 91%, precision of 90%, recall of 89%, and an F1 Score of 89.5%. They offer a significant improvement over traditional ML but still fall short of DynGAT's performance.
- **Hybrid Models** incorporate elements of both traditional and modern approaches, achieving an accuracy of 89%, precision of 88%, recall of 87%, and an F1 Score of 87.5%. While effective, they do not match the superior metrics of DynGAT.

So DynGAT's advanced use of dynamic graph structures and attention mechanisms allow it to achieve the highest performance metrics, making it a leading solution in the field of fake news detection.

Table 3. Comparison of Model Performance

Model	Accuracy	Precision	Recall	F1 Score
DynGAT	95%	94%	93%	93.5%
Static GNN	87%	85%	84%	84.5%
Traditional ML (Decision Tree)	82%	80%	78%	79%
Transformer-based	91%	90%	89%	89.5%
Hybrid Model	89%	88%	87%	87.5%

Error! Reference source not found. Table 4 provides several examples of outputs generated by the hybrid model utilizing Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and attention mechanisms for classifying news articles as either real or fake. Each example includes the input article, the model's classification, the associated confidence score, and key features identified from the text. These outputs illustrate the model's ability to discern between genuine news content and misleading information based on linguistic patterns and sensational language.

7. Conclusions

In this study, we introduced the Dynamic Graph Attention Network (DynGAT) for detecting fake news in social media networks. The DynGAT model effectively utilizes a dynamic graph structure to capture evolving interactions between users and news sources, combined with attention mechanisms to identify critical patterns of news propagation. We evaluated the performance of the DynGAT model using the TweepFake dataset, a comprehensive dataset of 20,712 samples, balanced between real and fake news articles.

Experimental results demonstrated that the DynGAT model outperformed baseline methods and state-of-the-art approaches, achieving an accuracy of 95%, precision of 94%, recall of 93%, and an F1 score of 93.5%. This represents significant improvements over traditional methods and other recent models in terms of accuracy and overall classification performance.

The primary contribution of this research is the integration of dynamic graph structures with attention mechanisms to capture evolving news propagation patterns in social media networks. By combining graph-based features with semantic text analysis, our approach offers a more nuanced and accurate mechanism for fake news detection. This research fills a critical gap in understanding the dynamics of misinformation spread on social media platforms and contributes to the development of more robust and effective fake news detection systems.

Table 4. Examples of News Article Classification

Input Article	*Classification*	*Confidence Score*	*Key Features Identified*
Breaking news: Scientists discover a cure for cancer! This groundbreaking research has been published in top journals and is set to revolutionize medicine.	Real	92%	"cure for cancer," "groundbreaking research," "revolutionize medicine"
Shocking evidence shows that the moon landing was staged. Experts reveal new documents that prove the government has been lying to us for decades!	Fake	87%	"moon landing staged," "experts reveal," "government lying"
Local baker wins national award for best cupcakes. The bakery has been serving the community for over 20 years.	Real	95%	"national award," "serving the community"
Scientists warn that eating chocolate can cause extreme weight loss. This shocking discovery has gone viral on social media.	Fake	90%	"extreme weight loss," "shocking discovery," "gone viral"
The President announces a new policy aimed at improving healthcare for all citizens. This policy is expected to make healthcare more accessible and affordable.	Real	89%	"new policy," "improving healthcare," "accessible and affordable"

Future research can explore further refinements to the DynGAT model, such as incorporating additional features from external knowledge sources, adapting the model to different social media platforms, and enhancing interpretability and explainability. This will enable greater transparency and user-understandability of the model's decision-making process, thereby improving trust in its predictions. Overall, our findings demonstrate the potential of graph-based attention mechanisms in improving the accuracy, reliability, and interpretability of fake news detection models, and highlight their utility in combating misinformation in the digital age.

Declarations

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Authors' contributions

FJ: Study design, acquisition of data, interpretation of the results, statistical analysis, drafting the manuscript, revision of the manuscript.

Conflict of interest

The authors declare that no conflicts of interest exist.

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