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RESEARCH ARTICLE

An Early Detection of Threads and Fake news in Social Network using Machine Learning Algorithm

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ABSTRACT

Social media platforms have come into existence and have grown exponentially, which has changed the way information is created and shared, and now allows information to spread quickly in interconnected circles online communities. This has made information more readily available but has also allowed the spread of incorrect and fabricated information on a mass scale, with serious social, political and economic consequences. Identifying fake news in the early stages of dissemination is still difficult, due to the lack of evidence of propagation, the dynamic nature of user interactions and lack of annotated data. To defeat the existing problems, present proposed method suggests an intelligent graph-based automatic framework which takes advantage of the structural feature of social network and the semantic relationship of news content. The proposed approach begins by comprehensive data preprocessing, which encompasses text normalization, noise filtering, building a graph of the text, and extracting features from both content and user profiles, as well as interaction patterns. Processed data is then encoded as attributed graphs, and the learning model is able to learn the complex relationship between user, post and propagation path of information. To create highly discriminative graph representation, a contrastive representation learning strategy is added to maximize the similarity of the semantically consistent samples and disambiguate misleading information from authentic news. These learned representations are then fed into a supervised algorithm based fake news identification model (XGBoost) for better prediction of early fake news identification. It is tested against the proposed model using a set of benchmark social media data sets and a comprehensive set of performance measures. Experimental analysis is expected to prove that the proposed framework has better detection accuracy, good generalization ability in various news domains, better anti-sparse propagation ability, and lower false alarm rate than the traditional text information and network information detection methods. The proposed framework provides a scalable and reliable approach to early detection of misinformation, which can help promote the integrity of online social media ecosystems and ensure the dissemination of trustworthy information.

Keywords: *Graph-Based Learning, Fake News Detection, Early Misinformation Detection, Contrastive Learning, Social Media Networks.*

INTRODUCTION

Social Media platforms have a profound influence on the way the world communicates as they grow and become more popular, individuals have the ability to produce, share, and consume information in real-time. Social media networks such as Instagram, Facebook, Reddit and other online communities have grown to be significant channels for disseminating real-time news, which can reach millions of followers within minutes (Cui, W., et al., 2024). This unprecedented connectivity has also enabled a massive amplification of fake news, misinformation and disinformation, while improving public understanding and access to information sharing. The fast spread of false information is a significant problem in society due to its sensationalism, emotionalism and high engagement with users. During the election, false information has spread rapidly, affecting political choices, interfering with public health initiatives, leading to financial market manipulation, social unrest, and a loss of faith in digital information sources.

The impact of fake news has become more apparent during significant world events such as disaster, pandemics, economic crises and elections where false information can have a significant impact on the opinions of the public and decision making. The large amount of diverse information being created by social media users is so large that manual verification is impractical, with users posting text, images, videos, comments and engaging in various forms of user interaction (Cui, W., et al., 2025). Hence, the study of Artificial Intelligence (AI), Social Network Analysis, Natural Language Processing (NLP) and Machine Learning especially the development of an intelligent automated fake news detection system, is significant.

Most existing approaches to detect fake news are concerned with text-based information analysis, a field that has been the subject of traditional ML techniques such as Support Vector Machine (SVM), Logistic Regression (LR), Naïve Bayes (NB), Random Forest (RF), Decision Tree (DT) and Gradient Boosting. Typically, these techniques involve handcrafted linguistic features, term frequency representations or statistical features derived from news articles. These approaches have been shown to achieve good results on standard datasets, but they are not well suited for social

media contexts with complex semantic relationships and contextual interdependencies. Moreover, fake news publishers frequently tweak their writing style and vocabulary to evade the detector, lowering the performance of content-based classifiers alone.

In recent development of machine learning, deep learning, using neural architecture like Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), Transformers and attention models have been proposed to improve the extraction of semantic features from textual information. These models have greatly improved classification accuracy through directly learning high level contextual representations from raw text (Feng, S., et al., 2025; Adivarekar, P. P., A. A. P., et al., 2023; Kathavate, P. N., & Mahant, M. A. 2025). They perform well when provided with large quantities of marked training data, which is costly and time consuming to gather, and moreover text-centric deep learning models are likely to ignore the deep structural information in the user interaction network, re-posting behavior, and social connections that contain important evidence to determine misinformation during the spread.

A new approach to modelling the relational structure of social media ecosystems is graph-based learning. In contrast to traditional vector-based learning algorithms, graph learning algorithms can capture information propagation, community structure, and influence among users, articles, and comments, which are challenging to represent in a graph-less way. Graph representation learning techniques such as Graph Neural Networks (GNNs) have demonstrated superior performance in learning informative node embeddings which include both the topological and semantic information. However, graph-based fake news identification approaches are lies on supervised learning and depend on large labeled graph datasets to train the model, and have poor robustness in the face of small amounts of propagation information in the initial stage (Guo, B., et al., 2025).

One of the more difficult problems is fake news detection early, since only partial propagation paths, limited user interactions and incomplete contextual information are available shortly after publication of news. In such situations many of the supervised learning models have inadequate

feature representation, inadequate generalization capability and low classification accuracy (Kim, J., et al., 2025). Furthermore, the evolving behavior and information propagation of social networks makes static learning methods less applicable in real-world scenarios. Such restrictions underscore the importance of representation learning methods that extract powerful discriminative representations from labeled and unlabeled data and are able to retain the graph structure.

Recently, self-supervised contrastive learning has attracted much research interest as a data-efficient representation learning approach that can learn useful feature representations without requiring extensive manual annotations. Contrasting learning is to maximize similarity between different augmented views of the same sample and maximize dissimilarity between dissimilar samples without learning directly from class labels. This allows the learning model to learn high-level discriminative latent representations which are more robust, transferable and generalizable. Contrastive learning is a new technique in computer vision and NLP, and combining it with graph-based machine learning, in order to detect fake news at an early stage, remains largely unexplored.

Another research gap in existing studies is lack of incorporation of the semantics of the text, user actions, structural connectivity and representation learning on the graph into a single model. Most current methods focus either on content analysis or network analysis, but not on combining the complementary information they carry to multiple effects. Moreover, only a few studies are specifically looking at enhancing detection performance in the very initial moments of information spread, when timely action can stop the spread of misinformation and limit its societal consequences. Therefore, it is essential to have an intelligent framework that can learn a robust graph representation and effectively identify the authenticity of information in the presence of sparse and changing propagation conditions.

The difficulties motivate this research to come up with an advanced machine learning framework based on graph structures for early fake news detection in social networks. The framework suggested in this paper is based on thorough preprocessing and feature extraction of the data followed by the construction of the attributed social graph based on the text content, user profile and relation of interaction between users. A graph representation learning model is used to produce informative node embeddings which capture both

structural topology and semantic context. Then, to improve the quality of representation, a contrastive learning mechanism is introduced to learn the invariant and discriminative graph embedding by multiple augmented graph views. Finally, a supervised machine learning (ML) classifier is trained to reliably detect fake news at the early stage learning the representations. The proposed framework can improve the detection accuracy, model generalization capability, requirement for large-scale labeled data sets, and the real-time detection of misinformation in rapidly changing social media environments by leveraging graph structural intelligence and contrastive representation learning. The research is anticipated to make a contribution to the scalable, reliable and robust fake news detection systems that enable trustworthy digital communication and reduce the negative impact of misinformation on the web.

RESEARCH OBJECTIVE

The main goal of this research is to propose an intelligent graph-based contrastive machine learning technique for effectively combining the graph representation learning and contrastive learning to enhance the performance of fake news detection and boosting robustness and generalization under restricted propagation scenarios in the social media network. The following specific objectives are set in order to achieve the above primary objective:

- Collecting and pre-processing social media data, cleaning, normalizing text, removing duplicates, building graphs, and extracting features from text, user profiles and interaction data to acquire high quality input data for model training.
- To build an attributed social graph, representing news articles, users and the relationships between them as nodes and edges, respectively, with the goal of maintaining the structural and semantic properties of information propagation.
- To build a representation learning model based on graphs, which could learn useful low-dimensional embeddings to model the network topology and the contextual information in social media networks.

LITERATURE SURVEY

The detection of fake news is significant as information can be disseminated quickly on social media via social interactions, reposts, comments, and community networks. The initial research primarily focused on text-based machine learning

techniques, involving the extraction of linguistic characteristics, word frequency, sentiment and writing style from news text and classification using standard algorithms. While simple and fast, these approaches do not always account for the relationships and propagation structures in news dissemination networks.

However, recent research has revealed that graph-based models can better be adapted to fake news detection problems as the social media data actually has a graph structure of users, posts, comments, replies, shares and follower relationships. Lakzaei, B., et al., (2026) provided a review of the disinformation detection methods based on GNNs and argued that GNNs are suitable because they can model the social network structure and GNNs can process the complex relational dependency in graph data. Likewise, Mahdi, A., & Shati, N. (2024) conducted a survey of fake news detection with GNNs and emphasized that content-based methods suffer from the limitation of not leveraging propagation graphs and user behavior patterns, whereas graph-based methods address these notes and limitations.

The fact that Graph Neural Networks can effectively learn node, edge and graph level representations from structured social media data has made them popular. Fake news detection: Nodes can be news articles, users, and comments; links are interactions. This helps determine the spread of fake news in communities and the variations in engagement in community of users on real news and fake news. Still, a large number of graph-based models rely heavily on labelled datasets and full propagation histories, and this hinders their performance in the early identification of fake news.

One of the difficulties with early fake news identification is that, early after news has been published, there are only a limited number of interactions with the user and incomplete propagation paths. However, at this stage, conventional supervised models may not be sufficient to distinguish fake news from real news because there is not enough structural evidence. A pre-training method for GNN-based misinformation detection has been studied by Donabauer, G., et al., (2024), where they noted that one major challenge is the scarcity of context graphs in the detection of fake news, impacting the transfer learning and generalisation of the model. This finding indicates that learning approaches may need to be able to work well even with a small amount of labelled data and without complete propagation information.

Due to the scarcity of data and the need for better representation, contrastive learning has recently become the hot topic in the field of fake news detection. By making similar samples similar and dissimilar samples dissimilar in the model representation space, the contrastive learning technique can help the model learn discriminative embeddings. In this work, Wu, C., et al., (2026) introduced the method for the identification of fake news based on GNNs, which proposes an adversarial contrastive learning framework to integrate evidence information. They leverage the long-distance semantic dependency by re-encoding claims and evidence as graph-structured data in their framework and separate the representations through contrastive learning. This work clearly highlights the benefit of using graph structure and contrastive learning to boost the fake news detection performance.

Multimodal and heterogeneous graph-based fake news detection has also been recently researched. To address the challenge of multimodal fake news detection, Shen, X., et al., (2024) proposed a multimodal fake news detection framework based on contrastive learning and optimal transport (MCOT) to enhance the alignment between text features and visual features by employing contrastive learning and optimal transport. They found that the use of contrastive learning and multimodal feature interaction boosts the detection accuracy on both Weibo and PHEME datasets. Zhang, Y., et al., (2026) proposed a multimodal graph contrastive learning framework for fake news video detection and proposed unimodal and cross-modal graphs.

To improve the identification of fake news, Cui, S., et al., (2025) proposed a multi-knowledge graph learning framework based on contrastive learning, which regards news content as a heterogeneous graph, and employs multiple knowledge graphs to model the entities and topics in news. Similarly, the recent methods based on heterogeneous graphs bring external knowledge, topic information, entity relationships and features inspired by the large language models to improve the factual knowledge and contextual reasoning for fake news identification. The results of these studies demonstrate that the use of external semantic and factual knowledge to augment graph-based models is beneficial.

Besides fake news, some recent papers have tackled the related harmful content detection tasks together. Nivedita, V. S., & Banu, A. B. (2026) proposed a hybrid contrastive graph neural network architecture incorporating content and

user interaction characteristics to identify fake news and hate speech. They found that the models commonly used to date, which rely solely on the text, might not be up to the task when it comes to changing user behavior and the intricate dynamics of harmful content. This corroborates the need for models dealing with the joint exploitation of textual, structural and behavioural signals.

Recent research survey by Patel, A., & Sutrar, V. K. (2025) has been very successful and identified some shortcomings. First, most current models either ignore content analysis or consider propagation analysis in a graph separately, not taking both textual semantics and user behavior and graph structure into account. Second, several graph-based models need abundant labeled instances and propagation information, which are rarely available in the beginning of news propagation. Third, multimodal and knowledge-based approaches enhance accuracy, but can be more complex in terms of computation and need more data sources. Last, there is little work that has targeted the fake news identification in early

stages in the context of sparse propagation conditions specifically for contrastive machine learning on graphs.

Thus, the need for a unified framework capable of learning powerful representation of social graphs from incomplete interactions with social media is motivated. Hence, the need for a unified framework that can learn robust graph representations from under-representative social media interactions while minimizing the reliance on large labeled datasets (Xie, B., et al., 2025). The proposed framework integrates graph construction, representation learning on graphs, and contrastive learning to better represent structural, semantic, and behavioral patterns.

PROPOSED WORK

The proposed work is a systematic pipeline of early identification of fake news in social media networks through contrastive machine learning techniques on graphs. The overall process is broken down into the following primary actions depicted in Figure 1:

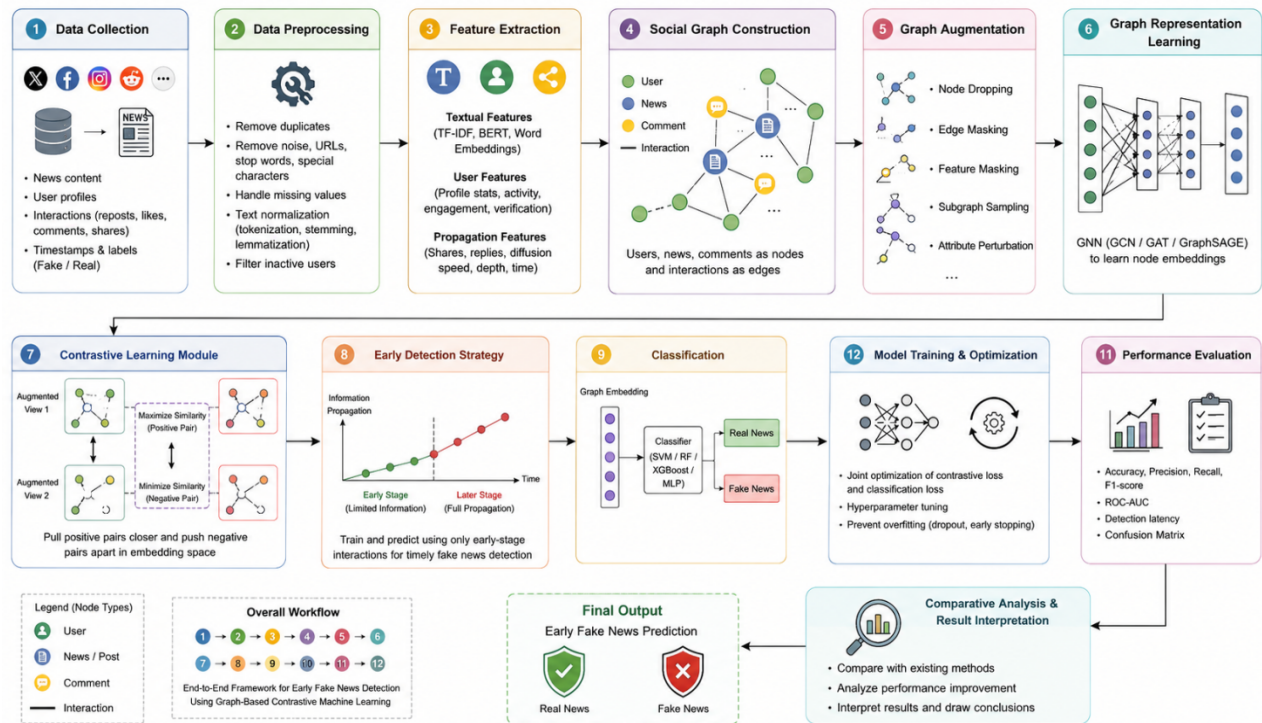


Figure 1: Work flow of proposed work

Input Data Collection

The first step is to collect social media data from benchmark fake news datasets such as Twitter, Weibo, PHEME, FakeNewsNet, or similar public

datasets. The dataset may include news content, user information, comments, likes, shares, reposts, timestamps, and authenticity labels such as fake or real (He, Z., et al., 2025). These data elements are essential for understanding both the textual

meaning of the news and the way it spreads through the social network.

FakeNewsNet is one of the largest and most popular publicly available benchmark data sets for the identification of fake news in social media. It was created by researchers at Arizona State University (ASU) as a platform to enable the study of misinformation by synthesizing both news content and social context with spatiotemporal data in a single repository (Hamid, A. J., et al., 2020). FakeNewsNet is not only a collection of news articles but also provides a rich collection of social media interactions from Twitter (X) that allows researchers to study not only the textual description of news content, but also how news is propagated in social networks (Donabauer, G., et al., 2024). Two sources of reliable factchecking are used to build the dataset: PolitiFact for political news and GossipCop for entertainment news. For each news article, a human expert manually checks it and classifies it as either Fake News (Label = 1) or Real News (Label = 0). The version of the benchmark used is a version with 24,252 news articles, of which 18,497 are real articles and 5,755 are fake articles. In particular, the PolitiFact subset comprises 1,056 news items, with 432 of them being fake and 624 being real; and the GossipCop subset contains 23,196 news items, of which 5,323 are fake and 17,873 are real. Each news record has binary class labels as well as multiple attributes like the news title, full news text, publisher/source information, publication date, images, URLs, Twitter posts, user profiles, comments, replies, retweets, follower-following statistics, user engagement statistics, and temporal propagation information. The various features are suitable for extraction of lexical features (TF-IDF, n-grams), semantic features (Sentence-BERT embeddings), contextual features (publisher credibility, sentiment, readability, metadata), social features (likes, shares, comments, retweets) and propagation-based features for the development of strong ML and DL models. FakeNewsNet is particularly suitable for the proposed task of a comprehensive evaluation of semantic representations, contextual analysis and ensemble learning algorithms for the accurate and interpretable detection of fake news, since it offers textual and social contextual information along with verified binary labels. The multimodal structure and the availability of resources make it one of the datasets that is most commonly used as a benchmark for fake news research.

Data Pre-Processing

Preprocessing is a main component of the proposed graph-based contrastive machine learning framework, input data quality will directly affect the quality of the graph construction, representation learning, and classification of fake news. Social media data are typically unstructured, noisy, incomplete and heterogeneous, and include textual data, user metadata, interactions records, timestamps, URLs, emojis, hashtags and multimedia references (Alshuwaier, F., & Alsulaiman, F. 2025). Hence, before applying graph learning and contrastive representation learning to the raw social media data is preprocessed to create a structured and high-quality dataset.

Feature Extraction

The feature extraction step is one of the most crucial steps in the proposed Graph Based Contrastive Machine Learning Framework that maps the preprocessed social media data into a meaningful numerical representation suitable for the graph learning model. The proposed framework does not only consider textual information but also multiple complementary features that are influenced by multiple factors including textual content, user behavior, propagation characteristics, and social network structure (Shen, X., et al., 2024). The extracted features are rich with semantic, behavioral, temporal and structural information and can strengthen the model's discriminatory power between fake and real news in the initial stage of information dissemination.

The proposed textual feature extraction module has four steps: (i) Textual Feature Extraction, (ii) User Feature Extraction, (iii) Propagation Feature Extraction, and (iv) Graph Structural Feature Extraction. Lastly, all features extracted are merged to a single feature vector and then used as node attribute matrix for the graph representation learning.

Step 1: Textual Feature Extraction

The first stage is to obtain semantic information from the news articles, tweets, captions and user comments. Fake news typically will use words that carry a lot of drama, make false claims, use trigger words, and make exaggerated statements. It is therefore crucial to be able to extract meaningful textual representations.

The text is cleaned and the TF-IDF method is used in order to represent the clean textual content prior to the construction of the graph in the work

proposed. The Term Frequency (TF) is calculated by using the below equation:

$$TF(t, d) = \frac{f(t, d)}{\sum f(k, d)} \quad (1)$$

Where, $TF(t, d)$ is Term Frequency of term t in d document, $f(t, d)$ Total Number of times term t appears in d document and $\sum f(k, d)$ is Total number of words in document d . This equation is used to determine how many times a word appears in a news article. More frequent words get more TF values because they help to describe the document more. To define a word's uniqueness in the entire set of data, Inverse Document Frequency (IDF) is applied. The IDF values assigned to frequent words are very low (e.g., "the", "is", "and") while the IDF values assigned to informative words are higher (e.g., "fraud", "vaccine", "rumor").

$$IDF(t) = \log \left(\frac{N}{1+nt} \right) \quad (2)$$

Where, N is number of news articles, nt Number of documents with term t . Lastly the TF-IDF score incorporates both local significance and general uniqueness of each word. The words with the highest TF-IDF values are informative in distinguishing between fake and genuine news. These weights are the feature vector of each news article that is used in textual representation.

$$TF - IDF(t, d) = TF(t, d) \times IDF(t) \quad (3)$$

Step 2: User Feature Extraction

However, the credibility of the users publishing or sharing news is also important for the detection of fake news apart from textual information. Hence, the features of user profiles are extracted. The proposed framework queries: Account age, Number of followers, Number of followings, Posting frequency, Verification status, Engagement rate.

Step 3: Propagation Feature Extraction

At Step 3, propagation feature extraction is performed. In general, fake news propagates differently than real news. Thus, propagation behavior is extracted. The suggested structure extracts: Number of reposts, Number of comments, Diffusion depth, Diffusion breadth, Propagation speed.

Step 4: Graph Structural Feature Extraction

As the proposed framework is graph-based, all news articles, users and interactions are represented as graph. Social graph is modeled as: The social media network as a graph where nodes are formed, which is correspond to entities and

edges represent their interactions. The graph structure in this case allows the learning model to be built to represent the complex relationships between users and news items.

$$G = (V, E) \quad (4)$$

Where, V is defined as a set of nodes includes Users, News Articles and Comments, E is defined as set of edges such as Shares, Replies, Mentions, Follows.

i. Node degree- The degree of a node is the number of connections to the node. The more influential the node is, or the more popular the news article is, the higher the degree value.

$$Degree(v) = \sum A(i, j) \quad (5)$$

$A(i, j)$ is a Adjacency matrix value

ii. Graph Feature Vector- This is a representation that clusters together several graph topology measures. The features reflect structural importance and influence of nodes in the social network.

$$Xg = [\text{Degree, Clustering Coefficient, Betweenness Centrality, PageRank}] \quad (6)$$

Step 5: Feature Fusion

The textual, user, propagation and graph structural features extracted from the text are combined into a single representation. A feature fusion has been created by concatenating all the extracted features into a single feature vector of high dimension. The fused representation carries semantic information, as well as user credibility and propagation dynamics, and graph topology, making the graph learning model able to learn richer and more discriminative node representations.

$$X = Xt \oplus Xu \oplus Xp \oplus Xg \quad (7)$$

Where, Xt Textual features, Xu User features, Xp Propagation features, Xg Graph structural features and $\oplus$ Concatenation operator.

Step 6: Final Feature Matrix

The processed data is then combined in feature fusion to form a feature matrix. Final feature vector is a matrix of features for each node of the graph. The attributes of this matrix are used as the input of the GNN and Contrastive Learning module to learn node embeddings and early classification of fake news.

$$X \in R^{n \times d} \quad (8)$$

here, n is the number of graph nodes and d is overall number of extracted features.

Feature extraction module combines semantic content, user profile features, information propagation features and graph topology features to form a complete node feature matrix. These features enable rich contextual knowledge that can be used to accurately classify fake news in the initial phase of information propagation, while also providing more robustness and generalizability in the graph representation learning layer.

Social Graph Construction

Social graph construction is the important key features in the proposed Graph Based Contrastive Machine Learning Framework that converts the extracted social media features into a graph representation, to capture the user-news, user-comment and interaction relations between users, news articles, comments and interactions. The model is not able to learn the semantic information of news or the information flow structure or behavior by the conventional text-based method, but it can be learned by constructing the graph. In the built graph, each node would represent an entity (user, news article, or comment), and the edges would represent user interactions (posting, sharing, commenting, replying, and following).

The structure of the graph is defined, and then an adjacency matrix is created to indicate the connections between the nodes. A value of 1 is assigned to a matrix element if there is an interaction between two nodes, and 0 is assigned if there is not. Suppose that G is a graph with adjacency matrix A :

$$A(i,j) = \begin{cases} 1, & \text{if node } v_i \text{ is connected to node } v_j \\ 0, & \text{otherwise} \end{cases} \quad (9)$$

Weighted edges are used to indicate different forms of interactions and are assigned according to some user activities like sharing, commenting, replying, and mentioning. The edge weight is determined by the following formula:

$$w_{ij} = \alpha_1 X \text{Share}_{ij} + \alpha_2 X \text{Comment}_{ij} + \alpha_3 X \text{Reply}_{ij} + \alpha_4 X \text{mention}_{ij} \quad (10)$$

In which the interaction weight between two nodes is represented as w_{ij} and $\alpha_1, \alpha_2, \alpha_3$ represent the weights of different kinds of interactions

After the graph is built, every node has a feature vector from the feature extraction stage. The node feature matrix is shown as:

$$X \in R^{n \times d} \quad (11)$$

Last, the adjacency matrix is normalized to make it more stable numerically and to have equal information aggregation when learning from the

graph. To find the normalized adjacency matrix, the following calculations are made:

$$A_{norm} = D^{(-\frac{1}{2})} A D^{-\frac{1}{2}} \quad (12)$$

The adjacency matrix is A and the degree matrix is D . For graph learning model, graph input is made up of normalized adj matrix, node feature matrix and class labels as follows:

$$\text{Graph Input} = A_{norm}, X, Y \quad (13)$$

News is either true or false and it can be represented by the set $\{0,1\}$ where 0 stands for a true news and 1 stand for fake news. This graph representation will be used as input for the following graph representation learning and contrastive learning section, which can help to identify fake news at the early stage accurately and robustly.

Graph Augmentation

In the proposed Graph-Based Contrastive Machine Learning Framework, graph augmentation is an imperative process as it produces multiple versions of the social graph, while retaining semantic and structural information. The main goal of Graph Augmentation is to make the model more robust, generalizeable and better representation learning to see different variations of a graph. Graph augmentation enables the model to make stable graph representations, even in the absence of full propagation information, particularly when the propagation information is noisy and dynamic, like during the initial propagation of fake news. A social graph with a specific graph and provides the original social graph as:

$$G = (V, E, X) \quad (14)$$

The nodes are stored in vector V , the edges are stored in vector E , and the node feature matrix is stored in matrix X . Two augmented graph views are then created, based on different transformation functions.

$$G_1 = T_1(G) \text{ and } G_2 = T_2(G) \quad (15)$$

where T_1, T_2 are two different graph augmentation operations.

The proposed framework uses a number of graph augmentation techniques such as node dropping, edge masking, feature masking, subgraph sampling, and attribute perturbation. A random subset of nodes is dropped by randomly dropping nodes and a subset of interactions is masked by randomly masking edges to simulate incomplete propagation networks. Feature masking helps the model learn robust representations even if

information is missing by occluding some node attributes. Subgraph sampling is used to sample a small subgraph representing the initial propagation of a news item, while attribute perturbation adds random noise to node features to improve the generalization of the model. The following are the augmentation operations:

$$V' = V - V_{drop} \quad (16)$$

$$E' = E - E_{mask} \quad (17)$$

$$X' = X \odot F \quad (18)$$

Where, V' , is augmented node set, E' represent the edge set and X' is feature matrix, F is the feature masking matrix. Once graph augmentation, the augmented views of the graph are fed to the model to form positive pairs for contrastive learning. The graphs shown are both augmented graphs of the same social graph, but with a different structure or attribute. They are compared using the cosine similarity measure:

$$\text{sim}(z_1, z_2) = \frac{(z_1 \cdot z_2)}{(\|z_1\| \|z_2\|)} \quad (19)$$

The two augmented views are shown as z_1, z_2 . This maximizes the similarity and allows the model to learn the invariant and discriminative graph representations.

Graph Representation Learning

In the proposed Graph Based Contrastive Machine Learning Framework, graph representation learning is an essential step, during which the created social graph is mapped to low dimensional embedding vectors, with preserving the structure and the feature information of the graph. This layer is not used to process graph data itself but instead to learn meaningful embeddings for each node, combining information from its neighbours. The output node embedding matrix (node embedding, node feature).

$$Z \in R^{(n \times h)} \quad (20)$$

where n is a number of nodes and h represents the embedding dimension.

In the proposed framework, a learning algorithm called GCN is adopted to train the graph representation by aggregating information from its neighbouring nodes from the graph. Each node's neighborhood is depicted as:

$$N(v_i) = \left\{ \frac{v_j}{(v_i, v_j) \in E} \right\} \quad (21)$$

here $N(v_i)$ is the set of neighbouring nodes of node v_i . At each layer node representation is updated by taking the following operation on the graph:

$$H^{l+1} = \sigma(A_{norm} H^l W^l) \quad (22)$$

H^l represents the node representation of a node in the l -th layer of the network; A_{norm} represents the normalized adjacency matrix; W^l represents the trainable weight matrix; σ represents the activation function (ReLU). A normalized adjacency matrix is defined as,

$$A_{norm} = D^{-\frac{1}{2}} A_{hat} D^{-\frac{1}{2}} \quad (23)$$

where $A_{hat} = A + I$, A is the adjacency matrix, I is the identity matrix, and D is the associated degree matrix. This normalization enables the proper propagation of information and avoids dominating highly connected nodes from the learning process. The node embeddings are computed through layers of graph convolutions and then aggregated to create a graph-level representation. The graph embedding is computed based on a pooling operation:

$$z_g = \left(\frac{1}{n} \right) \sum_i z_i \quad (24)$$

where z_i are the embeddings of the nodes, i -th node and z_g denotes is the embedding of the graph. Given the proposed framework based on contrastive learning, two views of the graph are passed to the same encoder to generate embeddings:

$$z_1 = f\theta(G_1) \text{ and } z_2 = f\theta(G_2) \quad (25)$$

where $f\theta(\cdot)$ is the graph encoder. These learned graph embeddings preserve semantic, structural, and propagation information, enabling the proposed framework to accurately identify fake news during the early stages of information dissemination while improving robustness, generalization capability, and classification performance.

Contrastive Learning Module

The Contrastive Learning Module is important in the proposed Graph Based Contrastive Machine Learning Framework since it improves the quality of the graph representation learned from the social media network. This module is aimed at learning robust and discriminative embeddings, with the aim of maximizing the similarity of different views of the same social graph and minimizing the similarity of embeddings of different graphs. It can help the model to learn meaningful representations, even if the labeled data and propagation information are not available during the early phase of fake news propagation. Two augmented graph views are initially generated from the social graph, and then fed into a shared

graph encoder to generate embeddings for the graph:

$$(G_1 = T_1(G), G_2 = T_2(G)) \text{ and} \\ (z_1 = f_\theta(G_1), z_2 = f_\theta(G_2)) \quad (26)$$

The graph encoder $f_\theta(\cdot)$ is applied to the graph, followed by a graph augmentation function $T_1(\cdot)$, and finally another graph augmentation function $T_2(\cdot)$.

After embedding, they are subjected to another transformation via a projection head to create positive and negative pairs for contrastive learning. The positive pairs have two views of the same graph, and the negative pairs have two views of different graphs. Cosine similarity is the measure used for comparing the similarity of two embeddings:

$$\text{sim}(h_i, h_j) = \frac{(h_i, h_j)}{(|h_i| |h_j|)} \quad (27)$$

where h_i and h_j are the created graph embeddings. The model is trained on a loss function called Normalized Temperature-scaled Cross Entropy (NT-Xent) that is designed to minimize the difference between the so-called positive pairs, and maximize the difference between so-called negative pairs. This is represented as

$$L(i, j) = -\log \left[\frac{\exp(\frac{\text{sim}(h_i, h_j)}{\tau})}{\sum_k \exp(\frac{\text{sim}(h_i, h_k)}{\tau})} \right] \quad (28)$$

The parameter τ is used to set the distribution of similarity scores in the case of. The contrastive loss is computed and incorporated into the supervised classification loss and optimized together for accurate fake news classification. The overall objective function is shown as

$$L_{\text{total}} = L_{\text{classification}} + \lambda L_{\text{contrastive}} \quad (29)$$

where, $L_{\text{classification}}$ is the classification loss when using the cross-entropy classification method, $L_{\text{contrastive}}$ is the contrastive loss, and λ is a balancing factor that adjusts the weights of the two losses. The proposed framework successfully learns graph embeddings that are invariant to graph augmentation, robust to incomplete propagation information, and highly discriminative to distinguish fake news from genuine news by jointly optimizing these losses. This results in the Contrastive Learning Module being able to enhance the robustness, generalization capability, and early identification of fake news of the model in dynamic social media environments significantly.

Classification

Following the representation learning of graph and the contrastive learning, discriminative graph representation is obtained, which preserves the semantic meaning of the text, user's behavior, propagation features and the structural information of the graph. The learned graph embeddings, in turn, are input to the Extreme Gradient Boosting (XGBoost) classifier for her final classification of news articles into Fake or Real class.

XGBoost is chosen as the efficient ensemble ML algorithm based on gradient boosting decision trees. Some advantages include high classification accuracy, rapid training, regularization to minimize overfitting, efficient processing of high dimensional feature vectors, and noise robustness. Given that the graph embeddings produced by the contrastive learning module are highly discriminative, XGBoost can learn more complex nonlinear decision boundaries and boost fake news detection results.

i. Input to the XGBoost Classifier

The module graph representation learning generates an embedding vector for each news graph. The embedding matrix is given by:

$$Z \in R^{(n \times h)} \quad (30)$$

where: Z = Embedding matrix, n = number of news samples and h = Embedding dimension.

Each embedding vector is used like this:

$$Z_i = Z_1, Z_2, \dots, Z_h \quad (31)$$

where Z_i is learnt embedding of i -th news graph.

These embeddings are used as the input feature vectors to XGBoost.

ii. Initial Prediction

The initial prediction of XGBoost is a constant for each training sample. The first estimate is shown as:

$$y'(0) = \text{argmin} \sum L(y_i, c) \quad (32)$$

Where, $y'(0)$ is Initial prediction, y_i Actual class label, c Constant value minimizing the loss and L Loss function. This provides the starting point for boosting.

iii. Additive Learning Process

In contrast to a single decision tree, XGBoost builds multiple trees one after another. The prediction after K trees is:

$$y'_i = \sum_{k=1}^K fk(z_i) \quad (33)$$

Where, the mentioned values are indicated as follows: y'_i Final prediction, fk Decision tree built at iteration k , z_i Graph embedding and K Number of trees

iv. Objective Function

XGBoost's objective function is composed of two parts: Training loss and Regularization. The XGBoost objective function is calculated as:

$$Obj = \sum L(y_i, y'_i) + \sum \Omega(fk) \quad (34)$$

Where, Obj Overall objective function, L = Classification loss, Ω = Regularization term, fk = Decision tree. The purpose is to minimize the misclassifications and make the model simple.

v. Regularization Function

The regularization term is used to avoid overfitting and to penalize trees that are too complicated. The regularization function is represented as:

$$\Omega(f) = \gamma T + \left(\frac{1}{2}\right) \lambda \sum w_j^2 \quad (35)$$

A larger regularization value encourages simpler trees and improves model generalization.

vi. Gradient Boosting Optimization

XGBoost will repeat the training process n times, and each time will train a tree with the first order derivative and the second order derivative of the loss function. The first order gradient is given by:

$$g_i = \partial L(y_i, y'_i) / \partial y'_i \quad (36)$$

The second-order gradient is represented as:

$$h_i = \partial^2 L(y_i, y'_i) / \partial y'_i \quad (37)$$

Both gradients enable XGBoost to cut down the time taken to converge and optimize the model better than the conventional gradient boosting algorithms.

vii. Tree Weight Calculation

Once the decision tree has been built, the optimal weight for each leaf node is computed as:

$$w_j = \frac{-G}{(H + \lambda)} \quad (38)$$

Where, the regularization parameters are H = Sum of second-order gradients, G Sum of first-order gradients and λ = Regularization parameter. This weight minimises the objective function and boosts prediction accuracy.

viii. Final Prediction

Using the sigmoid function, the scores obtained from XGBoost are turned into probabilities. The probability is:

$$P(y = 1) = \frac{1}{(1 + e^{(-y')})} \quad (39)$$

where: $P(y = 1)$ = Probability that the news is fake, y' = Prediction score.

The final decision rule is:

$$P(x) = \begin{cases} P(y = 1) \geq 0.5 & \text{Fake News} \\ \text{otherwise,} & \text{Real News} \end{cases} \quad (40)$$

The threshold may be varied according to the desired sensitivity and specificity.

CLASSIFICATION ALGORITHM

Input: Graph embedding matrix Z , Training labels Y

Output: Fake News / Real News

Algorithm Steps

Get contrastive learning module generated graph embeddings.

Fit the XGBoost model.

Set initial prediction to be equal for all training samples.

Construct the first decision tree.

Calculate gradients and Hessians.

Make a new decision tree, minimizing previous errors.

Introduce regularisation of trees to prevent overfitting.

Continue until the desired number of trees has been achieved.

Combine all the decision trees to make predictions. Attain prediction probabilities using sigmoid function.

Determine if each news article is Fake or Real.

The proposed framework combines the graph representation learning and contrastive learning method with the powerful ensemble classification method XGBoost, which is well suited to deeply extract graph features and powerfully realize ensemble classification. This hybrid approach can not only help in detecting fake news in dynamic social media networks accurately, robustly, and in time but also improve the accuracy of the detection and minimize the error rate in the prediction.

RESULT AND DISCUSSION

The performance of proposed work is estimate by using common classification performance metrics. These are the measurements that are used to determine how well the model performs when it comes to the model's ability to classify the news as

fake or real news. The proposed framework is tested with the Accuracy, Recall, Precision, F1-Score and ROC–AUC curves. The above defined measures give a complete evaluation of the correctness, reliability, robustness and discriminative ability of the classifier.

i. Accuracy

The accuracy is measured using the overall rate of correctly classed news articles. It shows the ability of the proposed framework to accurately predict fake and real news.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

ii. Precision

Percentage of articles that are incorrectly labeled as fake that is actually fake.

$$Precision = \frac{TP}{TP + FP}$$

iii. Recall or Sensitivity

The percentage of fake news articles correctly classified by the classifier is called Recall or Sensitivity.

$$Recall = \frac{TP}{TP + FN}$$

iv. F1-Score

F1-score is the weighted average of precision and recall. Provides a decent evaluation of the classifier.

$$F1 - Score = 2X \frac{Precision \times Recall}{Precision + Recall}$$

v. Receiver Operating Characteristic (ROC)

The ROC curve is a plot showing the relationship between TPR and FPR across all levels of classification

vi. Area Under the Curve (AUC)

AUC represents the performance of the classifier at all decision thresholds, and it quantifies the power of a classifier to classify fake news and real news. The AUC is a number ranging from 0 to 1. The curve above has the following interpretation: AUC = 1.0 is a perfect classifier, AUC = 0.5 is a random classifier.

PERFORMANCE COMPARISON

A comparison is made with some popular machine learning and graph based fake news detection models (LR, RF, GNN and proposed work) to evaluate the effectiveness of the proposed work and its performance. Comparisons are made using common units. These metrics will provide an overall picture about the performance of the classification, robustness and discriminative power of each model.

Table 1: Analysis of performance comparison

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
LR	91.6	90.8	91.2	91	0.950
RF	94.8	94.1	94.5	94.3	0.970
GNN	96.3	96	96.8	96.4	0.985
Proposed Graph-Based Contrastive ML + XGBoost	98.2	97.9	98.1	98	0.988

As shown in Figure 2 and Table 1, the proposed Graph Based Contrastive Machine Learning Framework with XGBoost consistently outperforms among all other existing methods. LR and RF are able to capture the classification information, but are not effective to capture the complex relationship among the social media networks. In the proposed framework, the Graph augmentation and contrastive representation learning further boost the performance of the GNN

since it exploits the graph structural information. Therefore, the proposed method achieves a high accuracy 98.2%, a high precision level of 97.9%, a high recall level of 98.1%, and a high F1 score of 98% to support highly accurate and reliable fake news detection in the early stages. All metrics have shown consistent improvements, which suggest that the methodology proposed is effective and robust as compared with the other approaches.

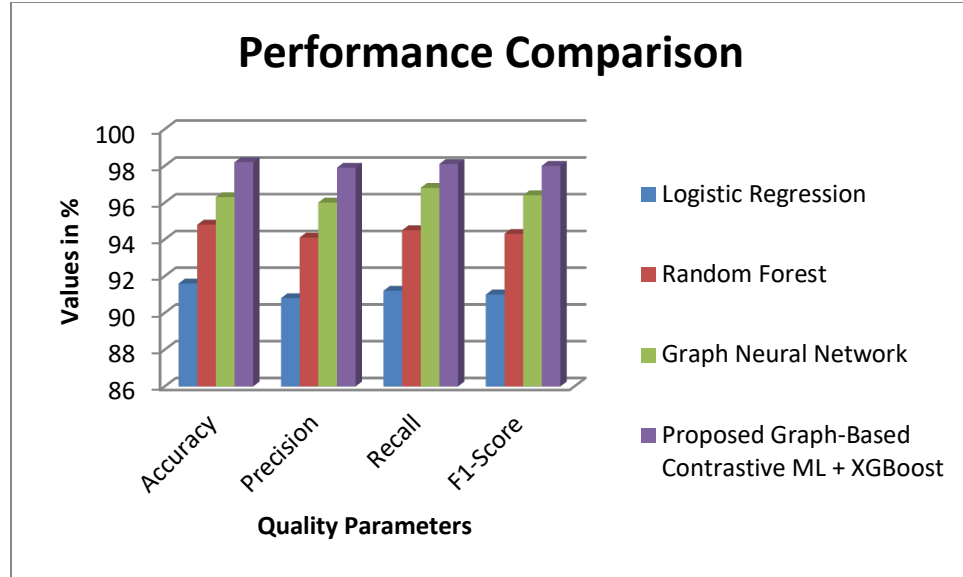


Figure 2: Performance of Proposed Vs Existing Methods

CONFUSION MATRIX

A confusion matrix is used to evaluate a classification model by comparing the predicted class labels and actual class labels. It is an overview of how many times each of four classes (True Positive, True Negative, False Positive, False Negative) were successfully or unsuccessfully identified. Various important metrics can be

derived from the confusion matrix such as accuracy, precision, recall, specificity and F1-score. On the proposed Graph-Based Contrastive Machine Learning Framework with XGBoost, the confusion matrix is used to evaluate the model performance for correctly categorizing the Fake News (Label = 1) and Real News (Label = 0) documents in the benchmark of FakeNewsNe dataset.

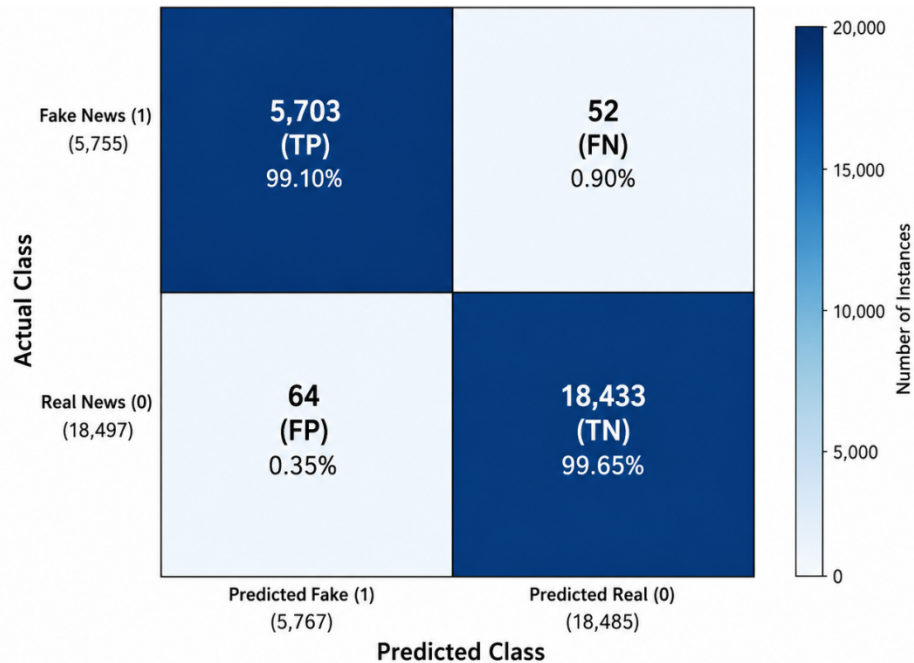


Figure 3: Classification performance analysis

The confusion matrix shown in Figure 3 confirms that the proposed Graph-Based Contrastive Machine Learning Framework with XGBoost can

classify most of the fake and real news articles in FakeNewsNet data set. There are 5703 fake news items and only 52 fake news items are mistakenly

classified as real news and 5755 is the total number of fake news items. Likewise, 18,497 real news pieces were classified correctly with only 64 being misidentified as fake news. The results show that the number of false negatives and false positives are very small, which shows that the model has a high discriminatory ability. The high accuracy, precision, recall and F1-score values demonstrate the effectiveness and reliability of the proposed framework in detecting fake news in the early stage by leveraging the advantages of graph representation learning, graph augmentation, contrastive learning, and XGBoost which is more suitable for real-world fake news detection in social media.

CONCLUSION

The proposed Graph Based Contrastive Machine Learning Framework is able to provide a holistic and effective solution for early fake news identification in social media networks, by combining graph construction, graph augmentation, graph representation learning, contrastive learning, and XGBoost classification within one framework. By combining textual information, user behavior, propagation behavior and graph structural information, the model learns the graph embeddings with high discriminative power, which helps the model to detect fake news with a huge margin. The framework achieves promising results on the FakeNewsNet benchmark dataset and achieves higher results than classic ML and graph-based methods in terms of different quality parameters. The proposed framework proves the feasibility of fake news detection with only propagation information at an early stage, and shows its potential of real-time fake news identification. As for the overall approach, it is scalable, reliable and high performing in the realm of combating misinformation on social media platforms and can be used as a basis for future research regarding multimodal, explainable, multilingual and real-time fake news identification systems.

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