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Graph Neural Networks For Relational Data Modeling And Optimization

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Abstract

The digital age news systems now employ relational data models to represent news items, together with users, sources, and assertions, as interrelated objects. However, there are some challenges that might be faced when using it, such as the appearance of fake news, multimodal fake news, and Artificial Intelligence (AI) news without any context. To solve such challenges, we present the model called the Elephant Herding Optimization-Enhanced Graph Neural Network (EHO-EnGNN) that integrates Graph Neural Networks (GNNs) and Elephant Herding Optimization (EHO). Evaluation of the suggested model can be done with the help of the fake news dataset available on Kaggle, where both real and fake news examples are provided. Data preprocessing can be done via tokenization, lemmatization, and the Term Frequency–Inverse Document Frequency (TF-IDF) is used for feature extraction. Next, a graph model is built to represent the relationships between news articles, users and other entities, leading to better embeddings and classification results. The code is implemented in Python using TensorFlow, PyTorch, Compute Unified Device Architecture (CUDA), Deep Graph Library (DGL), CUDA Deep Neural Network library (cuDNN), and Scikit-learn in Jupyter Notebook and Visual Studio (VS) Code. The model's performance is promising with F1-score of 0.956, accuracy of 0.956, recall of 0.952, and precision of 0.960 in comparison with other models. In summary, the proposed method enhances the detection of fake news with enriched relational representations, graph learning and optimization.

Keywords: Relational Data Modeling, Fake news detection, Artificial Intelligence (AI), Information Analysis.

1. Introduction

Relational data modeling is a structured approach to data management, enabling databases to be organised in tables that are linked through primary keys and foreign keys, and to be queried through Structured Query Language

(SQL). This approach performs well for the fake news detection, as it supports integration of different kinds of related information such as articles, sources, authors, and user actions by enabling comprehensive analysis of fake news patterns. This model facilitates the representation and analysis of connections between news, users and sources of information. Social media is the leading means of disseminating news, facilitating fast communication, but its interactive and engaging features might lead to the propagation of false news [1]. Existing fake news detection and link prediction approaches focus on textual and structural features, but tend to overlook external factors such as credibility and socio-political factors [2]. In this sense, relational data modeling offers a powerful approach to combine data from various sources and model relationships. Fake news not only deceives individuals but also causes social hysteria, affects elections and harms reputation. Multimodal fake news, which includes text, image and video, adds another layer of complexity to the identification process [3]. Graph theory has been proven to be quite useful in Artificial Intelligence (AI) driven fake news detection [4]. Additionally, in pandemic situations, fake news can undermine public health by disseminating disinformation [5]. The speed at which such information is transmitted, often motivated by curiosity and timeliness, plays a role in "infodemic" events [6]. To combat these threats, sophisticated detection models need to go beyond perceptible features and include linguistic, semantic and psychological factors [7]. Here, relational data modelling and the Natural Language Processing (NLP) plays a vital role in dealing with structured and unstructured data. In particular, text classification facilitates the automatic classification of news articles according to characteristics like topic, sentiment, and intent, and are therefore extremely useful in detecting inconsistencies and patterns that can signal fake news [8].

Research Aim: The aim of the research is to enhance detection of fake news by using relational data modelling together with the Elephant Herd Optimization-Graph Neural Network (EHO-EnGNN) algorithm. For this particular research, more attention will be paid to constructing a model that can incorporate information regarding the interrelation between different entities present in news articles.

Research Organization: Section 1 gives an introduction to the basic elements of fake news detection, relational data modeling, and Elephant Herd Optimization-Graph Neural Network (EHO-EnGNN) algorithm. Part 2 is concerned with the literature review, along with research gaps identified in the course of review. Section 3 defines the flow of the methodology used in this research, which includes data collection, preprocessing, feature extraction through TF-IDF, modeling of a graph, and EHO-EnGNN. Section 4 is devoted the presentation of results. Lastly, Section 5 outlines the findings of this research.

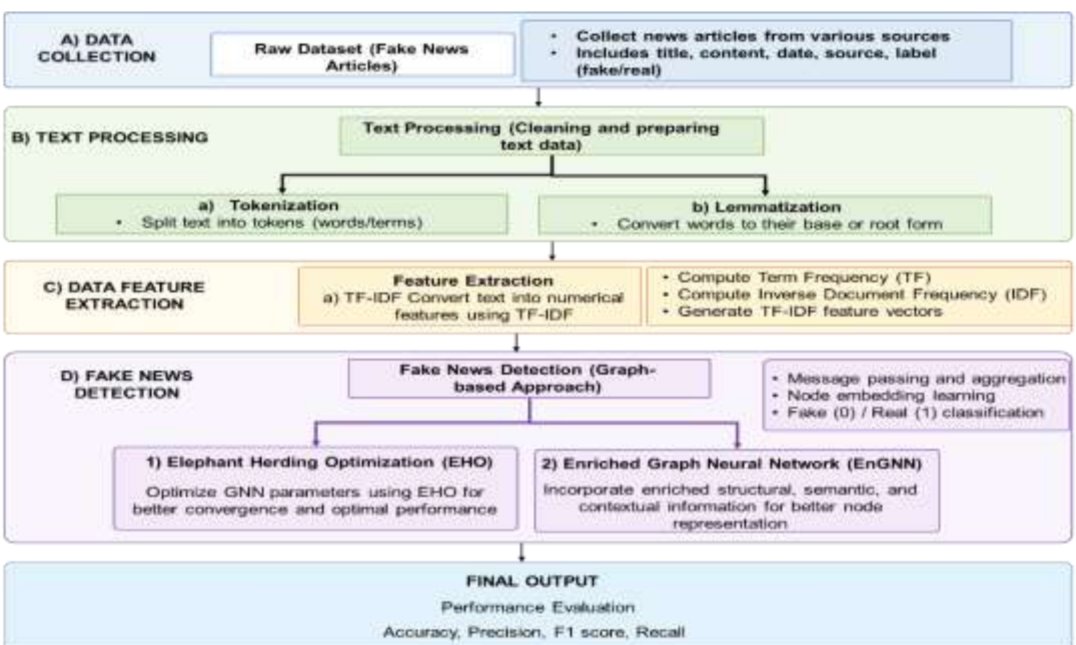
2. Related works

Research [9] suggests Enhanced Bidirectional Encoder Representations from Transformers (BERT), an method which employs multiple task learning for the detection of fake news in NLP. The enhanced model incorporates named entity recognition, relation classification, and stance detection with hierarchical attention and consistency loss and yields improvements in accuracy by 2.17% and 1.03%. Despite its effectiveness, the enhanced BERT model tends to be expensive and complex. Semantic Relationship-based Consistency and Inconsistency Balancing Network (SR-CIBN) model identifies multimodal disinformation on Social Media with contrastive learning and triplet loss to maintain the consistency and inconsistency factors related with fake news. The model achieves great accuracy levels of 0.908 on Twitter and 0.916 on Weibo and outperforms other existing models, albeit at a higher cost [10]. Spectral Graph Deep Learning model with Gated Recurrent Unit (SGDM-GRU) model improve the dynamic and historical graph structure in the detecting fake news. SGDM-GRU approaches achieves relatively high levels of accuracy, ranging from 97% to 98%, although it struggles with depicting real-world social graph dynamics [11]. Deep Learning (DL) approaches was employed for the detection of fake news in AI domain. In particular, residual networks and the multi-head attention mechanism are applied to generate alignment between multimodal features. The proposed approach demonstrates a superb performance in Accuracy (0.977) and F1-score (0.924). DL models do have greater accuracy and f1-score than Extended Language Representation model (XLNet), BERT, Robustly Optimized BERT Approach (RoBERTa), Enhanced Representation through Knowledge Integration (ERNIE), and Generative Pre-trained Transformer (GPT-3.5). Nonetheless, it is necessary to invest considerable computational power when training such models [12]. A graph-based approach was suggested to detect fake news in AI by the use of knowledge graphs, and Graph Attention Networks (GAT). Thus, a model is promising with an F1-score of 95% has been created, which demonstrates better results compared to classic Machine Learning (ML) techniques and DistilBERT. Nonetheless, the implementation of such models involves greater complexity [13]. On the other hand, an intelligent fake data detection system for smart cities, which utilizes optimized feature selection and ensemble learning, was developed. Moreover, a highly accurate model with the latency of 16 ms was trained for University of New South Wales Network-Based 2015 (UNSW-NB15) dataset [14]. Modified Transformer Network (MTN) was introduced using the use of synthesized multimodal fake news data and Particle Swarm Optimization–Differential Evolution Optimization (PSODO), which performs better than baseline methods, including CNN and ImageBind, with an accuracy of 90.42% and 86.74% for the Fakeddit and Deep Graph Model (DGM4) datasets, respectively, but it has high complexity and difficulty in parameter adjustment [15]. An AI-based method that uses fine-tuned language models in conjunction with emotion embeddings helps solve information asymmetry issues. The Cross-View Attention Architecture (CVAA) reaches an accuracy of 0.62, showcasing its excellent generalization capabilities despite its complex feature extraction mechanisms [16]. The Multi-Modal Multi-Dimensional Data Understanding and Situation Awareness (M3DUSA) model increases the effectiveness for the detection of fake news using multimodal approaches that achieves an F1-micro score of 0.962, yet, it had no established fusion method for different data types [17]. The Dual Stream Graph Augmented Transformer (DSGAT) approach integrates text and graph features, exhibiting outstanding performance on the FakeNewsNet dataset; still, it does not support multilingual and multimodal applications and requires further improvement in credibility assessments [18]. The Attention-based Knowledge Graph and Weighted Graph Convolutional Network (A-KWGCN) method leverages multimodal content analysis alongside network models to represent user interactions. Experiments conducted on Twitter15 and Twitter16 data sets reveal that the accuracy of the proposed method was 0.905 and 0.930, respectively, which surpasses other approaches like Support Vector Machine-Time Series (SVM-TS), modified Gated Recurrent Unit (mGRU), Decision Tree Classifier (DTC), Capture Score Integrate model (CSI), DEep Fake News Detection model (DEFEND), Representation Learning Model for Rumor Detection using Embedding (Rumor2vec), Generative Adversarial Network (GAN), and Graph-Based Context-Aware Attention Network (GCAN). However, the limitation with this approach is that it relies on knowledge graphs, whose completeness poses a problem [19].

3. Methodology

The proposed approach begins with obtaining the Kaggle fake news data, performing the data preprocessing methods including tokenization, and lemmatization.TF-IDF is used for feature extraction. Graph Neural Network (GNN) is employed to learn embeddings and understand relationships. Elephant Herding Optimization (EHO) is used to optimize parameters and improve model accuracy. Figure 1 depicts the proposed model which consists of data collection, text processing, feature extraction, fake news detection, and a final output as metrics.

Figure 1: EHO-EnGNN model for Fake News Detection



3.1 Data collection

Fake news detection dataset is obtained from the Kaggle source, (https://www.kaggle.com/datasets/emineyetm/fake-news-detection-datasets). It consists of 44,898 news samples, of which 23,481 fake news and 21,417 True news. For this experiment, dataset was extracted from reputable sources for fact-checking and news verification such as Politifact and GossipCop. Every record consists of a number of features like news title, text of article, published date, and a binary label. It is ideal for training and validating ML and DL method.

3.2 Text Processing using tokenization and lemmatization

Text processing in fake news detection entails structuring raw text processing such as tokenization and lemmatization. Tokenization helps in separating texts into meaningful units, while lemmatization assists in getting rid of inflected ends of words.

Tokenization: Tokenization is an essential procedure involved in data preprocessing in fake news detection, in which text is broken into more meaningful units referred to as tokens. The first thing done during tokenization is removing all punctuation marks that can exist in the text, but keeping important punctuation marks such as '@' and '#'. After lowering the text to lowercase, links, usernames, emojis, and hashtags become tokens by using Python libraries such as emoji. For example, the tokens of "The New American Century: An Era of Fraud" are: ['The', 'New', 'American', 'Century', ':', 'An ', 'Era', 'of', 'Fraud'].

Lemmatization: Lemmatization is an NLP method employed in detecting the fake information by reducing words into their base form or lemma form. This method allows the classification of various forms of words, such as "running," "ran," and "runs," as belonging to the base word "run."

3.3 Feature Extraction using Term Frequency–Inverse Document Frequency (TF-IDF)

Feature extraction can be carried out on the preprocessed data by employing the TF-IDF for the detection of fake news using the dataset. They contain details about news articles with columns: Title, Text, Subject, and Date. The TF-IDF can be used to transform text into a numeric representation. This give the important words more weight, or less important words less weight, as shown in Equation (1**).**

$$\omega(s_l) + se_l * \log\left(\frac{m}{ce_l}\right) \tag{1}$$

$s_l$is the l-th word in a news article from the dataset, $\omega(s_l)$is a base weight/smoothing factor allocated to terms, se_l is the Term frequency (TF), m is the total documents in the dataset**,** ce_l is the total documents in the dataset containing the label l, andlog $\left(\frac{m}{ce_l}\right)$ is known as the Inverse Document Frequency (IDF).

3.4 Fake News Detection Using Elephant Herding Optimization-Enriched Graph Neural Network (EHO-EnGNN)

EHO-EnGNN is a approach for detecting the fake news which integrates Enriched Graph Neural Network (GNN) with Elephant Herding Optimization (EHO). The EnGNN represents news articles, users, and sources as a graph to learn semantics and relations for fake news detection. Feature enrichment in multiple dimensions leads to better representation and learning complex social media interactions. EHO optimizes hyperparameters and features through a balance of exploration and exploitation, improving feature selection and noise reduction. Training is done with hyperparameter-tuned GNN layers, dropout, and adaptive learning rates for convergence. In summary, the combination of EnGNN and EHO greatly improves fake news detection accuracy and stability.

Enriched Graph Neural Network (**EnGNN)**: EnGNN classifies news from the dataset based on its accuracy, depending on how the nodes are integrated and related to each other. To further enhance the ability of the improved GNN to aggregate information and extract features, branch currents, important factors that indicate the properties of the fault, are added as multi-dimensional edge information. Regarding the detection of fake news, the EnGNN improves the capability of the approach to discriminate content by discovering complex relationships within the network of articles, users, and interactions.

$$H = (U, F) \tag{2}$$

Equation (2) is the graph representation equation, where H is the graph structure, which is also referred to as a heterogeneous or homogeneous graph based on circumstances, and U is a set of vertices or nodes within the graph. Fis the set of links or edges connecting nodes.

$$|U| \times |U|.W \tag{3}$$

Equation (3) represents the product of two matrices, |U | is a number of nodes in the graph, and W is a weight matrix or feature matrix associated with nodes or edges

$$G^{(l)} = E(B.\, G^{(l-1)}; \theta^{(l)}) \quad (4)$$

In Equation (4), $G^{(l)}$ is a embedding of the nodes at layer l, and $G^{(l-1)}$ is a nodes embedding at the preceding layer. B is the adjacency matrix defining the relationships among nodes, which dictates how information flows among neighboring nodes. $E(.)$ is the update function, which maps aggregated messages into new node embeddings. $\theta^{(l)}$ is the learnable parameters of the model at layer l. The propagation function for this network can be described by Equation (5)

$$G_{u_i}^{(l)} = \sum_{v_j \in M(u_i)} E(w_{u_i}^{m}, w_{u_i,u_i}^{f}, w_{u_j}^{m}, G_{u_j}^{(l-1)}) \quad (5)$$

$G_{u_i}^{(l)}$ is a embedding of the node u_i at the l -th layer of EnGNN.$v_j \in M(u_i)$ is a set of nodes are the neighbors of the node u_i,$v_j$is the individual neighbor node of u_i.$M(u_i)$ is a set of neighbors of the node u_i. $\sum_{v_j \in M(u_i)}$ adds up messages from all the adjacent nodes to represent node u_i. $w_{u_i}^{m}$is a node feature (state/memory) of the target node u_i.$w_{u_i,u_i}^{f}$is the edge feature between target node $u_i$and neighbor node u_j, which denotes the relationship characteristics.$w_{u_j}^{m}$ is the node feature of neighbor node u_j, $G_{u_j}^{(l-1)}$ is the embedding from the previous layer of neighbor node u_j.

Hyperparameter tuning with Elephant Herding Optimization (EHO): EHO algorithm is a type of nature-inspired meta-heuristic algorithm that is adopted to optimize feature selection using ISOT Fake News Dataset. This is a kind of swarm intelligence algorithm, and it is based on the inspiration drawn from the social life of elephants. This research involves adopting the EHO technique to optimize TF-IDF-generated feature vectors based on Fake.csv and True.csv news. EHO is an attempt to balance both the processes of optimization. On one hand, exploitation aims to refine the best properties of features for better accuracy in classification, whereas exploration aids in investigating a wide variety of TF-IDF properties.

$$w_{new,d_j}, i = w_{d_j}, i + \alpha \left(n_j - w_{d_j}, i\right) q \quad (6)$$

Equation (6) depicts the Clan Updating Operator (CUO), where i is the Index of the word, j is the Index of the news document in the dataset, d is the document in the fake news dataset,w_{new,d_j}, i is updated value of the weight for fake/real news classification, w_{d_j}, i is the current value of the weight ofnews document. α is the Learning Rate (LR), n_j is the value of the input feature value from Fake.csv and True.csv, and q is the Scaling Factor, for optimization in fake news detection

$$w_{new,d_j}, i = \beta\, w_{center}, d_j \quad (7)$$

Equation (7) depicts the Clan Center Influence (CCI), where β is the scaling factor that controls the influence. $w_{center}, d_j$is the central weight of the j^{th} document .w_{new,d_j}, i is the updated weight of the j^{th} document.

$$w_{Worst\,,d_j} = w_{min} + (w_{max} - w_{min} + 1)q \quad (8)$$

Equation (8) depicts the Separating Operator, where $w_{Worst,d_j}$is the updated weight of the least important word in the j^{th} document, w_{min} is the minimum possible weight value, w_{max} is the maximum possible weight value, where q is the random number typically in the range [0,1] used to generate or adjust weights.

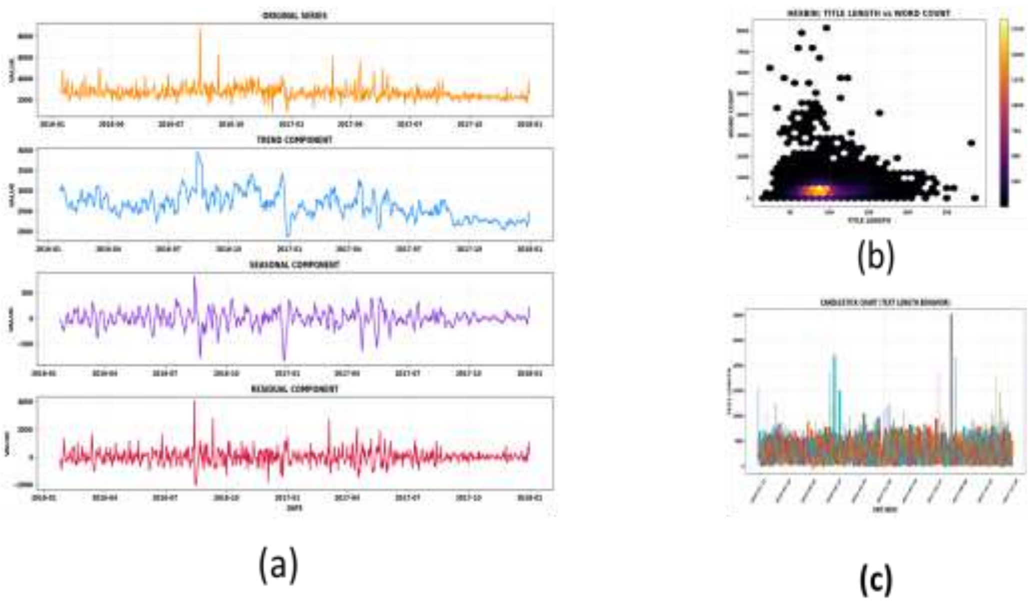
Hyperparameter configuration of the proposed EHO-EnGNN model: The EHO-EnGNN approach for fake news detection uses tuned hyperparameters for the graph learning, optimization, enrichment, and regularization. GNN has 2-4 layers with 64-256 hidden units, mean/max pooling, ReLU activation, and dropout (0.2-0.5) for regularization, batch size (32-128), Learning rate (1e-4-1e-2), and 50-200 epochs are used for training. EHO module uses 20-50 elephants in 3-10 clans, with parameters α (0.3-0.8), β (0.1-0.5), and matriarch influence, and 30-100 iterations for optimization. The enrichment module increases feature dimensionality by 20% - 50% and weights node edges 0.5-1.5. Adam optimization method along with cross-entropy loss function and early stopping (patience = 10 to 20) ensures smooth convergence and enhances the precision of detecting fake news.

4 Result

The proposed method was experimented on a computer that has CUDA 11.x with cuDNN installed on Windows 10/11 (64-bit) operating system. Model training involved Python 3.9+ along with TensorFlow, PyTorch, PyTorch Geometric, and DGL. For Text preprocessing and result analysis, Scikit-learn, NumPy, and Pandas were used, while Matplotlib was employed for results visualizations.

Exploratory Analysis: Figure 2 shows the breakdown of the time series data into its different components. Figure 2(a) represents the original series, which is the initial set of data without any breakdown, that displays the raw data points for the whole duration. Figure 2(b) shows the Trend Component that indicates the direction of the trend of the data, which can be an upward or downward trend in the data series. Figure 2(c) represents the recurring patterns or cycles that exist in the time series data after excluding the general trend. This means that the sub-figure illustrates how the data exhibits cyclical variations over time.

Figure 2: (a) Time series decomposition using original data with trends, seasonal components, and errors. (b) Hexbin plot showing the relationship between the number of words in the title and words per unit. (c) Candlestick plot showing the time variations in the length of texts.



Evaluation Metrics: The Analysis of the EHO-EnGNN model for fake news detection includes metrics specifically accuracy, F1 score, precision, and recall. Accuracy indicates how effectively the technique detects fake news. Precision on the other hand indicates how effectively the EHO-EnGNN method detects fake news without any mistakes.

Performance Evaluation: EHO-EnGNN model surpasses all previous models, which include DTC, SVM-TS, mGRU, CSI, dEFEND, Rumor2vec, GAN, GCAN, and A-KWGCN [19], in terms of capability for detecting fake news in ML domain. The proposed model of EHO-EnGNN surpasses the perform ance of current methods in terms of fake news detection, scoring f1 Score at 0.956, recall at 0.952, accuracy at 0.956, and precision at 0.960. This proves the superiority of the method in comparison to traditional approaches through balancing precision and recall, as depicted by Table 1 and Figure 3 below

Table 1: Evaluation comparing Existing Models and Proposed EHO-EnGNN for Fake News Detection

Model	Accuracy	F1-score	Precision	Recall
DTC [19]	0.561	0.562	0.575	0.537
SVM-TS [19]	0.693	0.692	0.693	0.691
mGRU [19]	0.661	0.556	0.560	0.562
CSI [19]	0.661	0.630	0.632	0.631
dEFEND [19]	0.702	0.631	0.637	0.638
Rumor2vec [19]	0.848	0.840	0.827	0.836
GAN [19]	0.854	0.870	0.861	0.847
GCAN [19]	0.908	0.759	0.759	0.763

A-KWGCN [19]	0.930	0.879	0.882	0.879
EHO-EnGNN	0.956	0.956	0.960	0.952

Figure 3: Model Evaluation Measures from Different Techniques to the proposed EHO-EnGNN Approach to Counter Fake News

4.1 Discussion

The classical methods, such as DTC [19], SVM-TS [19], mGRU [19], CSI [19] and dEFEND [19], suffer from certain challenges that involve their inability to capture the relations between data to detect fake news. The main drawbacks of DTC are weak generalization and incapacity to deal with large feature space in text data. Although SVM-TS can potentially enhance the accuracy of the predictions, it does not have the required capacity to detect context that is required in the fake news detection, whereas mGRU and CSI, do not have enough capacity to handle long-term dependencies in texts. Finally, dEFEND uses external data sources, which is not possible when there is no additional data. Rumor2vec, GAN, GCAN, A-KWGCN and others approaches have some advantages, but still do not solve the problems. To overcome these challenges, the proposed EHO-EnGNN model offers an improved method to detect the fake news. The GNN and EHO components of the model capture the connections among the users, sources, news articles and in a graph. EHO helps fine-tune the model parameters, enhancing model convergence, stability, and preventing over-fitting. Similarly, incorporating semantic and structural connections also boosts the detection performance, leading to increased f1-score, recall, accuracy, and precision, and the approach is well suitable for Wide-ranging of fake news detection.

5. Conclusion

In this research, the developed approach includes the use of an effective EHO-EnGNN method to identify false information by utilizing the methods of data modeling.. GNNs used along with EHO, the suggested model provides effective representation learning and classification of news based on their interactions with users and other articles. From the experiments, the EHO-EnGNN model proves to be more successful compared to competing models, delivering superior performance in metrics such as accuracy (0.956), F1-score (0.956), precision (0.960), and recall (0.952). Additionally, the optimization methodology employed in this research maintains the stability and improves the efficiency in the modeling process. Overall, this paper emphasizes that combining relational data modeling, graph-based learning, and swarm optimization offers an efficient solution to mitigate misinformation in social networks.

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