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SGDM-GRU: Spectral graph deep learning based Gated Recurrent Unit model for accurate fake news detection

Aqeel Sahi [a,b,*], Mostfa Albdair [c,d], Mohammed Diykh [d,e], Shahab Abdulla [f], Hadi Alghayab [g,i], Kaled Aljebur [g], Sarmad K.D. Alkhafaji [e,h]

[a] School of Mathematics, Physics and Computing, University of Southern Queensland, QLD, Australia
[b] College of Engineering, Al-Shatrah University, Thi-Qar 64001, Iraq
[c] Engineering Faculty, Misan University, Misan, Iraq
[d] Engineering Technical College, Department of Cybersecurity, Al-Ayen Iraqi University, Thi-Qar, Iraq
[e] University of Thi-Qar, College of Education for Pure Sciences, Thi-Qar, Iraq
[f] UniSQ College, University of Southern Queensland, QLD, Australia
[g] TAFE SW, QLD, Australia
[h] College of Engineering, Department of Artificial Intelligent, Al-Ayen Iraqi University, Thi-Qar, Iraq
[i] Computer Technology Engineering, Al-Taff University College, Karbala, Iraq

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ABSTRACT

With the surge of diverse news content on social media platforms, the necessity to effectively identify and combat fake news has never been more critical. The spreading of fake information in society could damage and harm the reliability of information as well as mislead public perception. As a result, several machine-learning-based models have been designed as promising methods to detect fake news. However, existing models experience some difficulties in capturing dynamic and historical social graph characteristics. This study proposes a novel approach called the SGDM-GRU (Spectral Graph Deep Learning Model based on Gated Recurrent Unit) to identify fake news. The proposed SGDM-GRU model incorporates GRU and represents network news patterns as graphs. We conducted several simulations on four datasets. Results showed that the SGDM-GRU model performs better than recently published fake news detection models. The proposed model obtained 97%, 98%, and 98% accuracy with Weibo, Twitter, Politifact, and Cossipcop datasets. With a combination of spectral graph deep learning models, the proposed model delivers a new finding in news detection research.

1. Introduction

The digital age has significantly increased the occurrence of fake news, posing substantial challenges to public opinion, political landscapes, and financial markets (Castillo et al., 2011; Ma et al., 2015, 2018; Yang et al., 2012). The rapid spread of information across online and social media platforms significantly obscures the distinction between credible reporting and misleading content. This proliferation of fake news threatens the principles of free expression, democratic processes, and journalistic integrity (Castillo et al., 2011). For instance, the 2016 US presidential election was notably impacted by fake news, with misleading information spreading widely during the campaign (Ma et al., 2015; Yang et al., 2012). In the same way, the spread of misinformation during the COVID-19 pandemic in 2020 triggered significant stock shortages and severe disruptions in supply chains (Batailler et al., 2022; Khoo et al., 2020; Kipf & Welling, 2016; Mikolov et al., 2013; Ni et al., 2021; Raza & Ding, 2022; Shu, Mahudeswaran, Wang, Liu, 2020; Silva et al., 2021).

Fake News Detection process (FND) is also defined as rumour detection. FND aims to identify whether a news article has been intentionally or unintentionally manipulated using machine learning and AI technologies, regardless of its domain and topic. The use of AI technologies could warrant the prevention of the spread of fake news within social media platforms. Moreover, due to the fast access to the internet, FND has become a favourite topic for researchers, gaining increasing attention from both government security authorities and the scientific communities.

Given these challenges, effective fake news detection methods are critical. Current challenges in fake news detection include the dynamic and evolving nature of fake news, the difficulty of capturing contextual and temporal information, and the shortcomings of current models in

* Corresponding author at: School of Mathematics, Physics and Computing, University of Southern Queensland, QLD, Australia.
E-mail address: aqeel.sahi@unisq.edu.au (A. Sahi).

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effectively addressing the challenges posed by diverse data sources and languages. Machine learning techniques offer promising solutions. They leverage complex algorithms to identify unreliable or deceptive textual, visual, or multimedia information automatically.

Most FND approaches have been designed using AI approaches, particularly deep learning and machine learning models. Recently, there have been several integrations between graph theory and deep learning techniques, with the research focusing on tackling the limitations of classic deep learning models. These limitations are represented by the ability of those models to capture the relational and structural information from the given text. Several recent studies have shown that a combination of graph neural network approaches can handle these challenges associated with classic deep learning methods.

Although several machine learning methodologies have shown promising results in fake news detection, most of the models fail to capture relational and contextual information from social media data when the models are evaluated using a collection of data such as text and image. Recent studies showed that most models have struggled to obtain a high detection rate when text and image pairs are mismatched. Our proposed model, Spectral Graph Deep Learning Model based on Gated Recurrent Unit, addresses these issues. In this paper, we incorporate spectral graph deep learning to extract relational and contextual information from social media data by analysing how fake news is interconnected to its neighbouring news. This feature can enhance the predictive accuracy of fake news detection using networked relationships. Our key contributions include a novel deep learning model, integrating spectral graph characteristics with GRU model for improved detection, robust performance in mismatched information, resulting in superior experimental results using several evaluation metrics.

Recent studies have shown that graph structures reveal relationships of all sentences in texts, which can help accurately understand the context. For example, Wang, Yuhang, et al. (2021) suggested a graph based model to represent relationship among sentences as a graph. Then, they utilised a self-attention graph neural network to represent the local and global features of the text. Although the mentioned studies have extracted the relationships among sentences by graphs, there is still a demand to design a graph based deep learning model to extract the hidden relationships and how the sentences are connected. Based on our knowledge, there has been no research that employed spectral graph deep learning to model text (Li, Guo et al., 2021; Monti et al., 2019; Wang et al., 2023; Zhao et al., 2019).

To address these challenges, this study proposes a novel approach called the SGDM-GRU (Spectral Graph Deep Learning Model based on Gated Recurrent Unit) to enhance fake news detection. The SGDM-GRU model incorporates GRU and represents network news patterns as graphs, aiming to capture dynamic and historical social graph characteristics more effectively.

The primary contributions of this work are as follows:

1. Introducing the SGDM-GRU model for fake news detection.
2. Demonstrating the model's superior performance on four datasets.
3. Highlighting the potential of spectral graph deep learning models in advancing fake news detection research.

2. Related work

Various methods have been proposed to detect fake news, which can mainly be divided into different categories. Natural Language Processing (NLP) models are used to analyse text content for fake news detection using methods such as sentiment analysis, topic modelling, and the identification of linguistic features (Mikolov et al., 2013). While these techniques are effective at examining text-based information, they may face difficulties with multimedia content and understanding context. Graph-based approaches use graph structures to show the connections between entities (such as users and posts) and identify fake news using network analysis (Silva et al., 2021). These approaches can recognise relationships and propagation patterns. However, they are computationally heavy and often require large datasets. Hybrid models integrate different techniques, such as NLP and graph-based approaches, to enhance detection accuracy (Xing et al., 2021). While they take advantage of the strengths of different approaches, they also add an extra layer of complexity and resource demands. Deep Learning (DL) models use complex neural networks, including CNNs (Convolutional Neural Networks) and RNNs (Recurrent Neural Networks), to detect fake news (Raza & Ding, 2022). In pattern recognition, DL models provide high accuracy. However, they require substantial labelled data and significant computational power. Another approach that analyses user behaviour to study user interactions and behavioural trends to detect fake news (Uppada et al., 2022). This method can detect fake news, but it compromises users' privacy and requires extensive user data.

The following paragraphs will discuss these approaches, including their benefits and drawbacks.

Relying on several factors, a study highlighted signal detection theory and how it may help understand what affects our beliefs about fake news. These factors include political bias, thinking carefully about information, and previous exposure to similar news (Batailler et al., 2022). Another study proposed a new DL model that uses behavioural information to enhance fake news detection accuracy (Xing et al., 2021). Zhao et al. (2020) studied the use of topological features to build ML models that effectively target and detect fake news. A transformer-based model that utilises news content and social opinions is also proposed. This model aims to improve early detection and achieve higher accuracy than traditional models (Raza & Ding, 2022). Shu, Mahudeswaran, Wang, Liu (2020) pointed out that hierarchical spread networks are crucial for developing social signals that help identify fake news effectively. Another model was proposed that utilises user engagement data and authenticity scores. It mainly focuses on users' social engagement to help identify fake news and accounts (Uppada et al., 2022). Ni et al. (2021) proposed the MVAN (Multi-View Attention Networks). Authors claimed that this model can better detect fake news on social media than current models. (Silva et al., 2021) used GNN to track how fake news spreads in different areas.

The use of graph-based DL has increased in detecting suspicious activities, including fake news. One notable example is the Temporal Graph Convolutional Network, which combines Graph Convolutional Networks (GCN) to analyse spatial patterns and GRU to capture temporal dynamics. This model shows the effectiveness of GCN and GRU in understanding the essential connections between space and time, which help analyse the spread of fake news. Li, Guo et al. (2021) developed a model incorporating geographical interactions through a weighted graph alongside a convolutional GRU network. This approach underscores the significance of geographical context in understanding spatial relationships. It provides valuable insights for enhancing the SGDM-GRU model by integrating relevant contextual information related to fake news distribution. Furthermore, a comprehensive study reviewed DL applications across various sectors, highlighting its advantages over traditional machine learning approaches (Alom et al., 2019). This research shows that advanced deep learning methods, like SGDM-GRU, can effectively detect fake news.

HGNNs models (Heterogeneous graph neural networks), also named multi-relational, are specialised graph neural network (GNN) models. It has been designed to model and process heterogeneous graph data. HGNNs include multiple types of edges and nodes and represent various interactions and relationships. HGNNs employ a unique formation of heterogeneous graphs to learn more significant features, making them more efficient for complex data with different relationships and entities. Recently, HGNN-based models have drawn researchers' attention to analysing complex data. For example, Zhao et al. (2024) applied HGNN to capture interactive information. Li et al. (2024) proposed model to recognise Skeleton action using HGNNs. Wang et al. (2022) proposed a recommendation model for Massive Open

Online Courses. In that study, HGNN was employed to model the data and extract useful information. Guan et al. (2023) improved HGNNs and integrated with the meta-path subgraph learning model. Additionally, Wang et al. (2023) introduced a graph-embedding-based model for detecting code vulnerabilities using a bidirectional gated graph neural network, demonstrating the advantages of merging bidirectional recurrent mechanisms with GRU to enhance learning. This concept could be adapted to boost the SGDM-GRU model's learning capabilities. A summary of diverse studies, including their methodologies and limitations, is presented in Table 1. In this study, we also integrated GRU with spectral graph convolutional networks (SGCN) that focus on classifying network information. The GRU models provide higher prediction accuracy than traditional models, such as LSTM (Mateus et al., 2021; Yang et al., 2020). Several other references also contribute to this field (Dong et al., 2020; Lafta et al., 2016, 2020; Leus et al., 2023; Ortega et al., 2018; Sahi et al., 2015, 2018).

Due to the widespread dissemination of misinformation on social media platforms, Fake news detection has become a critical research area. Various datasets have been used to facilitate the study of fake news, including Gossipcop and Plolitifact, that provide comprehensive repositories with news content, social context, and spatiotemporal information (Dou et al., 2021). Additionally, user preference-aware models have been proposed to enhance the detection of fake news by considering user behaviour and preferences (Ortega et al., 2018).

The insights can be drawn from various relevant studies to develop an accurate fake news propagation detection model. The proposed model can benefit from integrating the SGDM with the capabilities of the GRU neural network to address the limitations of previous models. By gaining insights from these studies, the SGDM-GRU model can increase the strengths of SGDM and GRU to effectively capture the complex spatiotemporal relationships inherent in fake news propagation, leading to more accurate detection outcomes.

3. The SGDM-GRU architecture

This section explains the proposed model for detecting fake news. Fig. 1 shows the main architecture of the model and how we modelled the propagation as a network. The characteristics of various node types are incorporated into the graph, which serves as input to SGDM for feature convolutional embedding. Firstly, the model converts each data graph $G = G_1, G_2, \ldots, G_n$. Then, produces features set for each graph $G(t), f(t) = f_i(t), \ldots, f_n(i)(t)$ for using the input embedding. The sum of $f(t)$ and $S(t) = s_i(t), \ldots, s_n(i)(t)$ which represent memory vector nodes, is fed into SGDM to obtain node features. Then, the obtained $\underline{f}(t) = \{\underline{f}_i(t), \ldots, \underline{f}_n(i)(t)\}$ is fed to the GAR unit. The SGDM model works on the Eigen-decomposition of graph Laplacian. The SGDM includes graph convolutional layers to learn short-term and long-term spectral graph representations. The SGDM is linked to a hidden layer that utilises a Relu activation function, which is incorporated into the GRU.

3.1. Problem formulation

For fake news modelling, let each dataset be represented as a set of graphs $G = G_1, G_2, \ldots, G_n$ where n denotes the total number of events included in the dataset G_i which represents the ith propagation network news. For each dataset, G_i, it was represented as $G(V_i, E_i)$ an undirected graph, where $V_i = v_1, v_2, \ldots, v_n$ represents a set of node's features, and $E = e_1, e_2, \ldots, e_m$ is a set of edges connecting the graph's nodes which show the relationship between the responded tweet and retweet. In this paper, each tweet is represented by a node v_i, n refers to the number of relevant tweets in a graph G, m is the observed interaction events. The set of features representing tweet v_i is denoted by $f \in R$. Each edge $e_{(i,j)}$ refers to a response between node v_i, v_j. The adjacency matrix A of graph G is represented as:

$$A(i,j) = \begin{cases} 1 & \text{if } e_{(i,j)} \in E, \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

A news network is formulated as follows: news propagation is denoted as $G(t) = V(t), E(t)$, where $V = \left\{ v_1^{t(1)}, v_2^{t(2)}, \ldots, v_n^{(t(n))} \right\}$ is a set of nodes, and $E = \left\{ e_1^{t(1)}, e_1^{t(2)}, \ldots, e_m^{t(m)} \right\}$ is a set of edges at a time t. Each node $v_i^{t(i)}$ denotes that the tweet v_i is posted at a time t, and each edge $e_j^{t(j)}$ denotes that the node v_i responds at a time t. The interaction events between node v_i, and node v_j is modelled as $e_{(i,j)}^t$ the total number of tweets is denoted as $n(t) = |v(t)|, m(t) = |E(t)|$ is the total number of interactions including retweets, and replies at the time t.

Each graph G_i is associated with the truth label where $y \in \{0, 1\}$. When $y = 0$ means truth news, while $y = 1$ denotes fake news. In this study, we formulated the fake news problem as: Given a news propagation network, $G(V(t), E(t))$, we aim to learn the mapping function $f : f(G(t)) \rightarrow y$ to classify the class of $G(t)$ using the corresponding interaction.

3.2. SGDM networks

The SGDM works on the relation between the graph nodes, as shown in Fig. 2. In this study, we adopted spectral SGDM, which works on eigenvalues of graph Laplacian (Batailler et al., 2022; Mikolov et al., 2013). Given an adjacency matrix $D = (d_{i,j}) \in \mathbb{R}^{NxN}$ with a weighted edge, the Laplacian of D is denoted as:

$$L = I_n - d^{-0.5} D d^{-0.5}, \quad L \in \mathbb{R}^{N \times N} \tag{2}$$

where D denotes the adjacency matrix, while d represent a diagonal matrix with $d_{i,j} = \sum_j D_{i,j}, I$ is the identity matrix of nxn. The eigendecomposition of L is defined as:

$$L = V \Lambda V^T, \tag{3}$$

where $V = [v_1, v_2, v_3, \ldots, v_n]$ represents n eigenvectors of L, and $\Lambda = [\mu_1, \mu_2, \ldots, \mu_n]$ refers to the eigenvalues of L.

Kipf and Welling (2016) proposed a graph filter. The generated graphs, which are represented by an adjacency matrix, are used as a filter for the input signal x. The output of the filter is computed using the convolution of G and x as shown below:

$$Y = g(L)x = g(V \Lambda V^T)x = V g(V) V^T x, \tag{4}$$

where g is the spectral representation of V.

As the number of nodes in a graph grows, the computational complexity of calculating g escalates accordingly. Polynomial expansion is employed in this paper to reduce complexity. The Chebyshev approximation is utilised to assess polynomial expansion using the following equation.

$$I_m(x) = 2x I_{m-1}(x) - I_{m-2}(x), \tag{5}$$

where $I_0(x) = 1$ and $I_1(x) = x$.

The local filter is defined as:

$$g_\phi = \sum_{i=0}^{f} \phi_f T_f(\underline{\Lambda}), \tag{6}$$

$$\underline{\Lambda} = \frac{2\Lambda}{\omega_{\max}} - I_n \in [-1, 1], \tag{7}$$

where $\underline{\Lambda}$ denotes to the scaled eigenvalues.

The Chebyshev expansion utilises $\underline{x} = 0$ and $\underline{x}_1 = \underline{L}x$ to minimise the computation time, where $\underline{L}$ refers to the normalised graph Laplacian. A filter f is employed to prevent overfitting and to update Y.

$$Y = \phi \left(I_n + d^{-0.2} D d^{-0.2} \right) x. \tag{8}$$

The eigenvalues lie in the interval [0,2]. As a result, the normalised adjacency matrix is defined as follows:

$$\underline{D} = D + 1, \tag{9}$$

$$\underline{d}_{i,i} = \sum_j \underline{D_{i,j}}. \tag{10}$$

Table 1
Summary of multiple studies in terms of methodologies and limitations.

Reference	Methodology	Limitations
Monti et al. (2019)	Geometric deep learning based social network structure and propagation patterns.	The study did not address the potential challenges or limitations of applying the proposed model to languages other than English or different social media platforms.
Yin et al. (2024)	Use graph autoencoder with masking and contrastive learning for unsupervised fake news detection.	Large, labelled datasets are required for graph-based techniques in fake news detection.
Balaanand et al. (2019)	Enhanced graph-based semi-supervised learning algorithm	The EGSLA algorithm has not been compared with other state-of-the-art algorithms in the field. The study does not discuss the computational complexity or resource requirements of implementing the EGSLA algorithm on a large scale.
Hsu et al. (2020)	GANs to generate fake-real image pairs, developing a network structure for pairwise learning.	CFFs may fail when new generator results have significantly different fake features. Difficulty in collecting training samples due to undisclosed technical details of some fake image generators
Nguyen et al. (2019)	Developing a graph-based method using Markov random field.	Limitations of the study include the existing deep-learning-based methods ignoring correlations among news articles, which the developed graph-theoretic method aims to address.
Dong et al. (2019)	Deep two-path semi-supervised learning model with supervised and unsupervised learning paths using convolutional neural networks.	Limited availability of labelled data for fake news detection. Lack of discussion on the generalisability of the model to other social media platforms.
Manavi and Zhang (2019)	The deep learning model for analysing network request behaviour.	The research acknowledges the limitations associated with employing definitive and static algorithms that were designed for small environments, particularly in the context of managing high-volume input and output data within distributed systems.
Wu et al. (2020)	Gated graph neural network algorithm.	The complexity of neural networks with many training parameters makes parameter tuning a tedious task.
Han et al. (2021)	Proposing a two-stream network for Deepfake detection in videos utilising RGB information and learnable SRM filters.	Lack of leveraging temporal information in existing Deepfake detection methods.
Sun et al. (2023)	Design a joint learning model named the HG-SL module.	Data limitation restricts the utilisation of certain features.
Shao et al. (2020)	Develop a detection system called FADE to identify fake accounts based on group behaviours	Focus on group-level detection may limit generalisability.
AbdElminaam et al. (2023)	Use a convolutional vision transformer.	Intention to work with divers datasets and generalise the dataset more with various augmentation techniques (self-reported limitations and suggestions for further research)
Cheung and Lam (2022)	Using multimodal source and propagation graph features for rumour identification, they used the Unified Multimodal Graph Transformer Network (UMGTN) with Transformer encoders.	The proposed method may not fully address all instances of missing features.
Mohammadrezaei et al. (2018)	Calculating similarity matrices, PCA, and balancing data with SMOTE.	Lack of consideration for the strength of the network of friendships.
Gowtham and Sreenivasulu (2021)	A novel lightweight verification algorithm.	Lack of physical protection for nodes.
Ahmed and Massicotte (2021)	Using a deep unfolded conjugate gradient architecture for large-scale MIMO detection.	The proposed architecture's performance sensitivity to initial parameter values and system parameters needs further investigation. The computational complexity reduction may require explicit knowledge of the training symbols.
Li, Xu et al. (2021)	A Mach–Zehnder fibre optic interferometer was used for signal collection.	Limited types of optical fibre vibration signals were studied.
Manzoor and Singla (2019)	Utilising a pre-trained recurrent neural net architecture.	The study may not generalise to all types of fake news articles as it only used four distinct openly accessible internet datasets.

Then, graph convolution is defined as:

$$Y = \phi\left(\underline{d}^{-0.2}\underline{Dd}^{-0.2}\right)x. \tag{11}$$

The idea behind the exponent of −0.2 is that the expressive power of the graph filter allows SGDM to approximate non-linear mappings from characteristics to labels on the graph. The expression power of SGDM is highly related to the choice of polynomials that are applied to approximate the graph filter. Three consecutive graph convolutional layers are employed in this paper. We also used a greedy algorithm to reduce the graph convolution complexity (Ni et al., 2021). The algorithm is designed to reduce the number of nodes by removing the isolated nodes and the nodes that have a similar set of edges. Then, max pooling is used to coarsen nodes that have no edges similar to those of counterparts into one node. The final graph is flattened and linked to a hidden layer using the Relu activation function. Table 2 list all hyperparameter values used in the proposed model.

Table 2
Hyperparameter of the proposed model.

Parameter	Value
Hidden layers	48
Filter type	Spectral Chebyshev filter
Node embedding dimension	10
Number of epochs	100
Activation function	ReLU
Learning rate	0.001–0.005
Batch size	64

3.3. SGDM coupled with GRU (SGDM-GRU)

In this paper, we utilised GRU for the detection phase. The GRU is a simpler structure, faster in the training speed, and provides a higher prediction accuracy compared with the LSTM network (Raza & Ding, 2022). The proposed SGDM model is integrated with GRU to detect fake

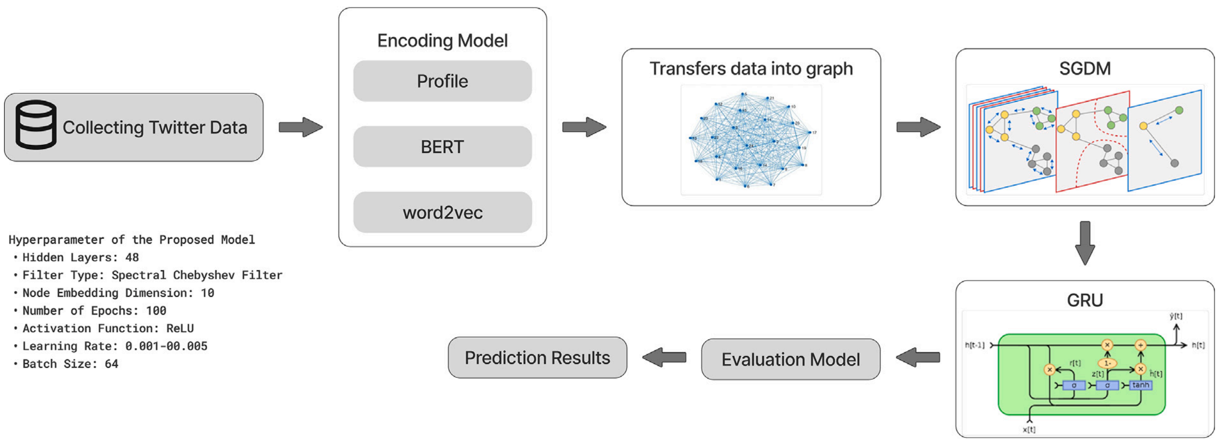

Fig. 1. The proposed SGDM-GRU model.

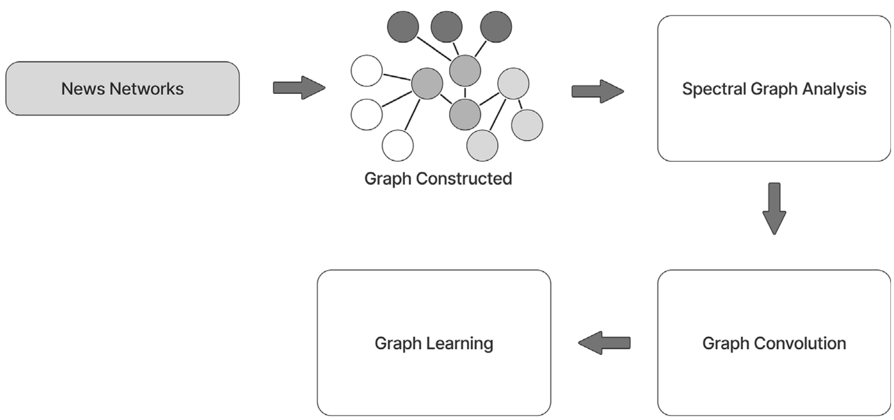

Fig. 2. The SGDM.

news. The input data of SGDM coupled with GRU at the time $t(t > 1)$, the output is $h(t-1) \in \mathbb{R}$ at time $t-1$. The main formula of the SGDM coupled with GRU is defined as:

$$\mathrm{GF}\left(T(t), G(t)\right) = \left[T(t), \underline{L}(t)T(t), \ldots, \underline{L}^{k(t)}T(t)\right] \emptyset, \tag{12}$$

$$\underline{L}(t) = I - d^{-0.2} L(t) D^{-0.5}, \tag{13}$$

$$L(t) = d(t) - G(t), \tag{14}$$

where d is the diagonal matrix, k is the hyperparameter, and $\emptyset$ refers to the weighted matrix of the convolution kernel. Then, $T(t)$ and $h(t-1)$ is concatenate to get $[T(t), h(t-1)]$, and $[g(t), k(t)]$ using graph convolution operation. To obtain the rest, get $rg(t)$ and update gate $ug(t)$; the $[g(t), k(t)]$ is split by the same volume. This process is expressed as:

$$[g(t), k(t)] = \mathrm{GF}([T(t), h(t)], G(t)), \tag{15}$$

$$rg(t) = \mathrm{sigmoid}(g(t)), \tag{16}$$

$$ug(t) = \mathrm{sigmoid}(k(t)). \tag{17}$$

After that, we did a product of $h(t-1)$ with $gr(t)$. Then the result is concatenated with $T(t)$ to obtain $[x(t), rg(t)\emptyset h(t-1)]$. Finally, the graph convolution phase is performed on $T(t)$, and $[x(t), r_g(t), \emptyset h(t-1)]$ as shown below:

$$i(t) = \varphi\left([T(t), r(t), \emptyset h(t)], G(t)\right), \tag{18}$$

$$b(t) = \tanh\left(\tanh\left(i(t)\right)\right). \tag{19}$$

To obtain the output $h(t)$, a weighted sum operation is performed using Eq. (20):

$$h(t) = ug(t)\emptyset h(t-1) + (1 - ug(t))\emptyset b(t). \tag{20}$$

The loss function, as shown in Eq. (21)

$$l = \frac{1}{nXa} \sum_{i=1}^{n} \sum_{j=1}^{r} \left| T^{*}_{i,j} - T_{i,j} \right|. \tag{21}$$

4. Experiments

4.1. Datasets

This section provides an overview of the chosen datasets to assess the proposed model. In this paper, we adopted four publicly available and real-world datasets. All datasets were collected from Sina Weibo and Twitter. These datasets include the following information: the text content, text content and temporal information, and propagation path. We provide some statistical information on these datasets in Table 3.

- **Weibo**: This dataset was employed for rumour classification and collected from the most common social media channel in China, Sina Weibo (Ma et al., 2015). The dataset contains a total of 2312 fake news and 2351 true news. We removed the news with timestamps and missing text.
- **Twitter**: This dataset was published in 2018 by Ma et al. (2018). The dataset includes two datasets under the names twitter_15 and twitter_16. First, picked non-rumours and true rumours from twitter_15 and real news and fake news from twitter_16. Then,

Table 3
Statistical information of the four datasets.

Dataset	No. of fake news	No. real news	No. users	Time length (h)	Average no. of tweets	Max no. of tweets	Min no. of tweets
Weibo	2131	2207	1,309,645	1577	378	19,999	10
Twitter	578	569	29,858	158	30	323	2
Politifact	157	624	23,865	1977	1200	5000	50
Gossipcop	2732	15 638	276 663	2137	500	10 000	10

pre-processed this dataset as we did with the Weibo dataset. Finally, consider the retweets, source tweets, and replies as graph's nodes and the interactions between tweets and replies as graph's edges.

- **Politifact**: The dataset was collected from the Politifact website (Shu, Mahudeswaran, Wang, Lee et al., 2020; Shu et al., 2017). The dataset covers a variety of domains, especially politics. Each news in the dataset is labelled as either real or fake. Table 3 details all information on the Politifact dataset.
- **Gossipcop**: The dataset contains a mix of fake and real news items (Shu, Mahudeswaran, Wang, Lee et al., 2020; Shu et al., 2017) The dataset is mixed of celebrity rumours and entertainment gossip. More statistics about the dataset are presented in Table 3.

4.2. Experimental setup and methodology

This paper randomly separated the datasets into 5 and 10 samples to conduct 5-cross validation and 10-cross validation. Each dataset is mapped as a hierarchical graph structure in which each root node represents news, and the leaf nodes represent a user. The edges of the graph represent tweets and responses. Each news event is represented as a graph. The data included in each raw news are {news context and news title}, while the user raw includes {user profile, user tweet, and context}. Several evaluation metrics were considered to evaluate the proposed model, including accuracy (ACC), precision (Prec), recall (Rec), and f-score (Abdulla et al., 2023; Al-Hadeethi et al., 2021; Alsafy & Diykh, 2022; Diykh et al., 2023, 2021; Lafta et al., 2018). MATLAB 2024b is used to implement the proposed model. The batch size was set to 128, and the learning rate was set to 0.001, refer to Fig. 1 for details.

$$\text{Accuracy (ACC)} = \frac{TP+TN}{TP+TN+FP+FN}, \tag{22}$$

$$\text{Precision (Prec)} = \frac{TP}{TP+FP}, \tag{23}$$

$$\text{Recall (Rec)} = \frac{TP}{TP+FN}, \tag{24}$$

$$\text{F-score} = 2\times\frac{\text{Precision}\times\text{Sensitivity}}{\text{Precision}+\text{Sensitivity}}. \tag{25}$$

4.3. Baseline models

The proposed SGDM-GRU model is compared against multiple baseline models, including traditional ML and DL models. The hyperparameters of all models were carefully selected. Baseline models are listed below:

- Decision Tree-based Model (DTM) by Castillo et al. (2011).
- Support Vector Machine-based Statistical Features model (SVM_SF) by Yang et al. (2012).
- A Linear Support Vector Machine Model (LSVM) by Ma et al. (2015).
- Neural Network Model (NNM) by Ma et al. (2018).
- Post-Level Attention Model (PLAN) by Khoo et al. (2020).
- Graph Convolutions Network (GCN) by Kipf and Welling (2016).
- Contextual Semantic Representation Model for Fake News Detection (CSFND) by Peng et al. (2024).
- Multi-scale Semantic Alignment based on Cross-modal Attention (MSACA) by Wang et al. (2024).
- Complementary Attention Fusion with an Optimised Deep Neural Network (CAF-ODNN) by Luvembe et al. (2024).

5. Results and discussion

In this paper, we encoded the raw news data using encoding approaches named Profile BERT and word2vec (Mikolov et al., 2013). That method was employed to encode the user profile and comments. The proposed model attained promising results on the four datasets. Table 4 reports the classification results using four datasets. The results were reported in terms of accuracy, recall, and f-score. The best performance obtained by the proposed model with the Twitter dataset scored ACC = 0.983, Recall = 0.985, and f-score = 0.985 with the Twitter dataset. It was observed in Table 4 that the encoding method had noticeable effects on the results. The results showed that the proposed model performed well with BERT over the four datasets, followed by the Word2vec method. However, the worst results were recorded by the proposed model with the Profile approach. The proposed model's extraordinary performance on the four datasets showed its capability to capture structural information to identify fake news. The proposed model could employ propagation patterns with user information to better identify true and false news. In addition, although we used different datasets, the performance of the proposed graph-based model did not struggle to effectively capture information from these datasets. For further evaluation, precision was also used to examine the proposed mode. Fig. 3 shows the proposed model's performance in terms of precision. The results obtained emphasised the advantages of employing spectral graph learning in extracting and analysing the propagation features of false news. They highlight the significance of combining spectral networks with deep learning to address the task of fake news detection.

5.1. Comparison with baseline methods

To demonstrate the proposed model's effectiveness, comparisons were made against several bassline fake news detection models. The comparisons with baseline models were presented in Tables 5–8. In this experiment, we conducted a comprehensive performance in terms of accuracy, f-score, and recall among the proposed method and other models. Our proposed model surpasses the other methods in Tables 5–8. The results showed that the proposed model scored the highest detection rate compared to other models. It scored the highest f-scores of 0.9205, 0.9921, 0.9642, and 0.9732 with Weibo, Twitter,Gossipcop and Politifact. The performance of all models was also assessed using receiver operating characteristic (ROC) curves. Fig. 4 reports the detection performance using ROC. The results showed the ability of the proposed model to detect fake news for different datasets. From the Comparison result, we can notice that the deep learning NNM, PLAN, and GCN baseline algorithm performed better than the traditional machine learning approaches such as DTM, LSVM, and SVM_SF. GCN obtained the second-highest detection rate. The results demonstrated the superiority of graph-based models in fake news detection. This confirmed the ability of the graph models to reveal important information in the data row of a dataset and how to employ that information to detect fake news from trustworthy news. In summary:

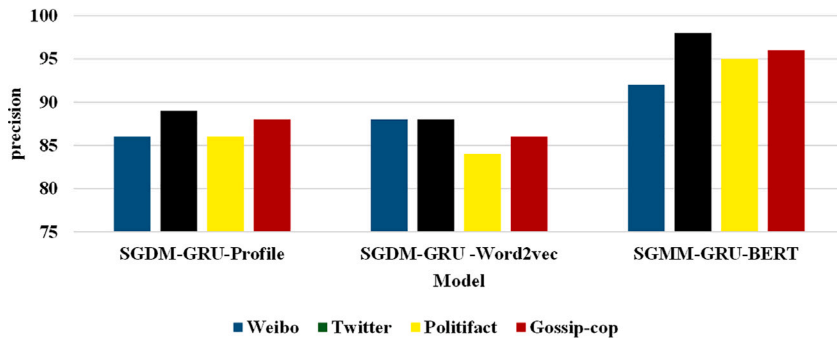

Fig. 3. Encoding evaluation models based on precision.

Table 4
Fake news detection results based on different encoding models.

Encoding model coupled with SGDM	Weibo			Fake Newsnet			Twitter		
	ACC	Recall	F-score	ACC	Recall	F-score	ACC	Recall	F-score
SGDM-Profile	0.887	0.875	0.865	0.875	0.886	0.883	0.897	0.906	0.898
SGDM-Word2vec	0.897	0.885	0.884	0.876	0.865	0.875	0.894	0.886	0.896
SGDM-BERT	0.901	0.897	0.896	0.971	0.974	0.973	0.983	0.985	0.985

Table 5
Fake news detection results using the Weibo dataset.

Model	Fake news				True news			
	ACC	REC.	F-score	Precision	ACC	REC.	F-score	Precision
DTM	0.7861	0.7732	0.7731	0.7643	0.7652	0.7543	0.7682	0.7633
SVM_SF	0.8121	0.8061	0.8142	0.8121	0.8030	0.8140	0.8023	0.8074
LSVM	0.8431	0.8412	0.8430	0.8436	0.8553	0.8580	0.8521	0.8559
NNM	0.8561	0.8560	0.8564	0.8548	0.8642	0.8680	0.8677	0.8609
PLAN	0.8668	0.8664	0.8623	0.8690	0.8764	0.8799	0.8754	0.8765
CAF-ODNN	0.8712	0.8709	0.8743	0.8721	0.8703	0.8712	0.8743	0.8708
MSACA	0.8675	0.8643	0.8678	0.8654	0.8743	0.8778	0.8798	0.8798
CSFND	0.8876	0.8868	0.8807	0.8843	0.8954	0.8909	0.8990	0.8945
GCN	0.8867	0.8767	0.8754	0.8775	0.8867	0.8854	0.8804	0.8894
SGDM-GRU	**0.9010**	**0.8970**	**0.9144**	**0.9084**	**0.9253**	**0.9199**	**0.9205**	**0.9273**

- The proposed model shows enhanced performance compared to all baseline models in terms of f-score, accuracy, and F1 score across four datasets, showing statistical significance. These results highlight the relevance of temporal propagation information in the verification of news authenticity.
- Graph deep learning models scored a higher detection rate than traditional machine learning models. Our investigation showed that the graph deep learning algorithms can extract complex patterns more automatically from the raw data than the traditional model using hand-craft features.
- Noticeably, the traditional models showed similar results in four datasets. There was no winner for them. The graph deep learning models, GCN and the proposed model, demonstrated comparable performance to the traditional deep learning algorithms, NNM and PLAN, over four different datasets. This was a sign that the graph deep learning models have better robustness than classic deep learning.
- The obtained results showed that all models had a slight delay in performance on the Weibo dataset. Our investigation showed there were many retweets in the Weibo dataset, and the node description was like the source node. However, the proposed model still outperforms baseline models by a significant increase in f-score and accuracy. The comparison results demonstrated the ability of graph deep learning to recognise fake news.

5.2. Ablation study

A number of simulations were performed in this section to explore how the characteristics of graph models influence the detection of fake news. More precisely, we conducted simulations to study the effects of global and spectral graph-based deep learning on the detection of fake news.

- Fig. 5 reports the detection rate in terms of accuracy and f-score. In this experiment, we compare the proposed model SGDM with the local graph deep learning model (LGDM). As we can notice from the results, SGDM outperforms LGDM across four datasets.

- To obtain a high detection rate, the parameters of the proposed model were investigated and tested to identify its effects on the detection rate. The hyperparameter β of graph convolution was tested several times, and the optimal values were selected in terms of accuracy and f-score. Fig. 6 shows the effects of β on the detection rate. From the obtained results, it was found that the highest detection rate was obtained when $\beta = 5$.

- The initial learning rate is set between 0.001 0.05. It was observed that the performance of the proposed model was improved when the number of epochs to 100. The batch size was determined based on complexity time and loss function, and it was set to 64. The node embedding dimension was set to 10, and the hidden dimension was set to 48.

- Another experiment was conducted to verify time stamps in the values $0, 10, 20, \dots, 80$ min. Tables 5–8 describes the accuracy of all models per time point on four datasets. From the results obtained, we can see that the proposed model performed better than other baseline models in detecting fake news across four datasets. The performance of the proposed model demonstrates obvious advantages as time goes on.

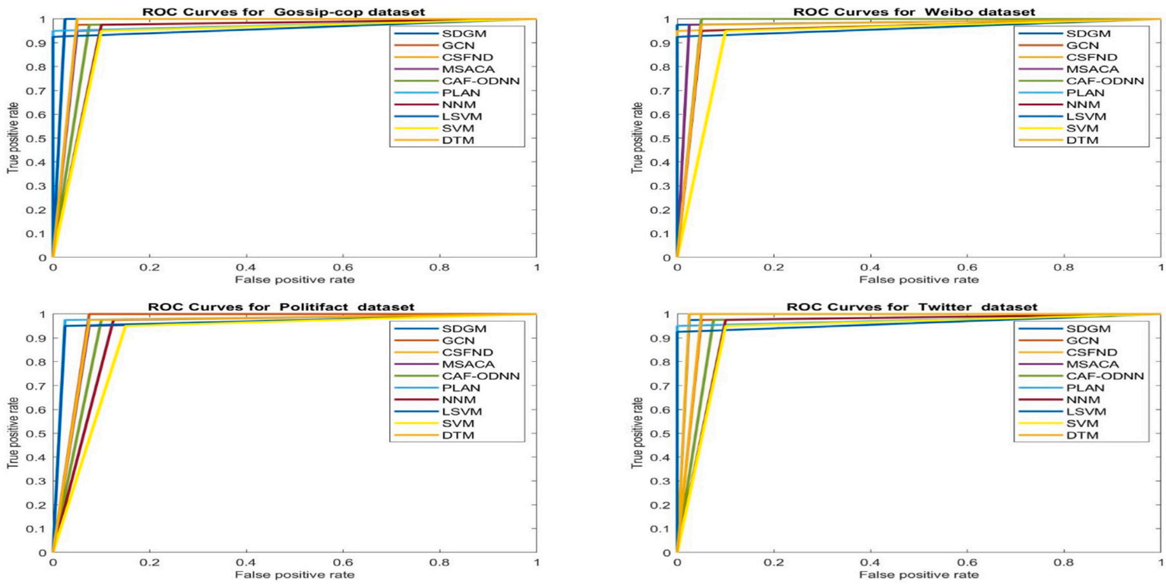

Fig. 4. Performance evaluation using ROC.

Table 6
Fake news detection results using the Twitter dataset.

Model	Fake news				True news			
	ACC	REC.	F-score	Precision	ACC	REC.	F-score	Precision
DTM	0.7942	0.7882	0.7843	0.7907	0.8123	0.8187	0.8143	0.8167
SVM_SF	0.8350	0.8312	0.8305	0.8389	0.8387	0.8387	0.8387	0.8391
LSVM	0.8724	0.8741	0.8850	0.8890	0.8907	0.8965	0.8994	0.8976
NNM	0.8970	0.8860	0.8924	0.8997	0.9087	0.9145	0.9198	0.9100
PLAN	0.8841	0.8835	0.8878	0.8843	0.8960	0.8964	0.8991	0.8976
CAF-ODNN	0.8856	0.8804	0.8812	0.8804	0.9320	0.8943	0.8933	0.8900
MSACA	0.8921	0.8902	0.8931	0.8932	0.9009	0.9076	0.9054	0.9065
CSFND	0.8905	0.8903	0.8943	0.8903	0.8976	0.8921	0.8932	0.8909
GCN	0.9040	0.9124	0.9020	0.9094	0.9252	0.9287	0.9205	0.9176
SGDM-GRU	**0.9837**	**0.9855**	**0.9854**	**0.9876**	**0.9897**	**0.9975**	**0.9921**	**0.9975**

Table 7
Fake news detection results using the Gossip-cop dataset.

Model	Fake news				True news			
	ACC	REC.	F-score	Precision	ACC	REC.	F-score	Precision
DTM	0.7831	0.7887	0.7890	0.7887	0.7765	0.7709	0.7765	0.7787
SVM	0.8432	0.8432	0.8454	0.8432	0.8576	0.8533	0.8570	0.8543
LSVM	0.8772	0.8709	0.8704	0.8703	0.8831	0.8861	0.8853	0.8843
NNM	0.9023	0.9087	0.9021	0.9021	0.9123	0.9103	0.9132	0.9125
PLAN	0.8974	0.8954	0.8943	0.8943	0.9034	0.9006	0.9043	0.9043
CAF-ODNN	0.8754	0.8744	0.8732	0.8741	0.8876	0.8865	0.8871	0.8821
MSACA	0.8871	0.8845	0.8856	0.8853	0.8976	0.8971	0.8978	0.8948
CSFND	0.8965	0.8954	0.8961	0.8951	0.9075	0.9086	0.9065	0.9064
GCN	0.9160	0.9154	0.9120	0.9122	0.9231	0.9234	0.9215	0.9141
SGDM-GRU	**0.9542**	**0.9541**	**0.9532**	**0.9521**	**0.9653**	**0.9651**	**0.9642**	**0.9621**

Table 8
Fake news detection results using the Politifact dataset.

Model	Fake news				True news			
	ACC	REC.	F-score	Precision	ACC	REC.	F-score	Precision
DTM	0.7654	0.7608	0.7610	0.7608	0.7621	0.7601	0.7564	0.7532
SVM_sf	0.8209	0.8281	0.8221	0.8265	0.8343	0.8378	0.8398	0.8398
LSVM	0.8376	0.8368	0.8307	0.8343	0.8354	0.8309	0.8390	0.8345
NNM	0.8821	0.8810	0.8843	0.8801	0.8901	0.9021	0.9031	0.9030
PLAN	0.8821	0.8865	0.8898	0.8867	0.8976	0.8976	0.8965	0.8979
CAF-ODNN	0.8650	0.8665	0.8650	0.8665	0.8860	0.8897	0.8861	0.8891
MSACA	0.8841	0.8876	0.8873	0.8897	0.9071	0.9076	0.9043	0.9054
CSFND	0.8876	0.8854	0.8865	0.8843	0.8909	0.8904	0.8994	0.8976
GCN	0.9072	0.9054	0.9054	0.9032	0.9121	0.9110	0.9112	0.9131
SGDM-GRU	**0.9634**	**0.9640**	**0.9643**	**0.9621**	**0.9754**	**0.9754**	**0.9732**	**0.9732**

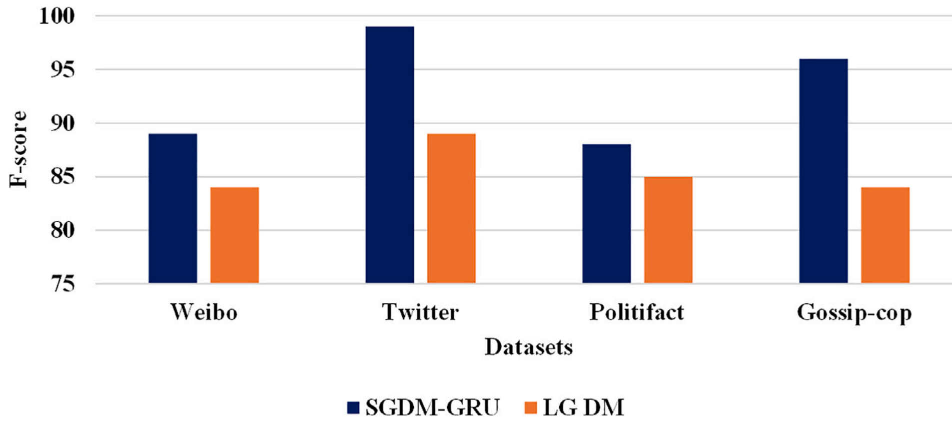

Fig. 5. The effects on the detection rate.

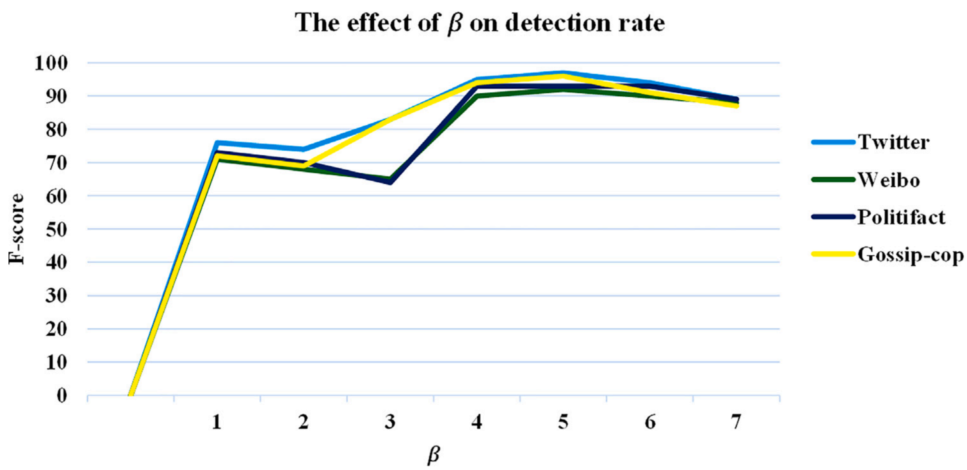

Fig. 6. The effects of β on the detection rate.

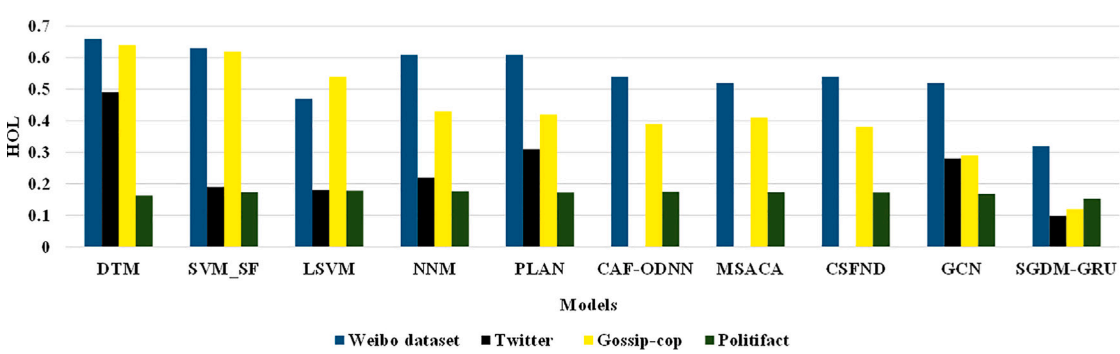

Fig. 7. Evaluation based on HLO metric.

- We utilised the Hamming loss metric to assess the performance of the proposed model. This metric evaluates the proportion of incorrectly classified human activities and ranges from 1 to 0, where a lower value signifies better performance. A score of 0 represents an ideal outcome. Fig. 7 illustrates the performance of all models in relation to Hamming loss. The findings in Fig. 6 underscore the effectiveness of the proposed model compared to existing models. The proposed model achieved the lowest HLO when compared to the state-of-the-art models.

5.3. Case study

Two case studies were discussed in this section to show the advantages of the proposed SGDM-GRU model. The scenarios were considered in this experiment, exhibiting that the proposed model has the potential to tackle challenges in real cases. For further evaluation, the proposed model was compared against recent studies named CSFND (Peng et al., 2024), MSACA (Wang et al., 2024), CAF-ODNN (Luvembe et al., 2024). This case study provides clear evidence to highlight the positive impact of using a spectral graph deep learning model to enhance the accuracy of the current news case. In this experiment, we considered the case (ID: politifact11115), which is labelled as a fake (0). This case study highlights the ability of the proposed model

Table 9
Running time comparison of each epoch.

Models	Weibo	Twitter	Gossip-cop	Politifact
DTM	1.2	0.4	0.9	0.7
SVM_SF	0.8	0.2	0.7	0.9
LSVM	1.3	1.1	1.5	1.5
NNM	2.9	1.8	2.1	2.5
PLAN	1.7	1.3	1.3	1.7
CAF-ODNN	2.2	1.8	1.6	1.8
MSACA	1.9	1.9	1.7	2.3
CSFND	1.6	1.6	1.5	1.8
GCN	2.5	2.3	2.5	2.8
SGDM-GRU	**11.2**	**14.6**	**10.3**	**6.4**

Table 10
Comparison with previous graph-based deep learning models.

Authors	Technique	Dataset	Feature	Accuracy
Weibo				
Bian et al. (2020)	Graph Global Attention Network with Memory (GANM)	Weibo	Graph user feature	0.9617
Chang et al. (2024)	GNN based on encoder model	Weibo	Graph feature	0.9765
Twitter				
Wei et al. (2021)	Bi-Directional Graph Convolutional Networks (Bi-GCN)	Twitter	Graph user feature	0.867
Politifact				
Monti et al. (2019)	Edge-enhanced Bayesian Graph Convolutional Network (EBGCN)	Politifact	Graph user feature	0.927
Dou et al. (2021)	Graph-based CNN	Politifact	Graph user feature	0.8462
Gossipcop				
Dou et al. (2021)	Graph-based CNN	Gossipcop	Graph user feature	0.9530
Multiple Datasets				
SGDM-GRU	**Spectral graph deep learning model based on GRU**	**Weibo, Gossipcop, Politifact, Twitter**	**Spectral graph features**	**0.92, 0.98, 0.86, 0.97, 0.98**

to enhance fake news detection compared to baseline models. The proposed model investigated how news articles were interconnected to their neighbouring news. This feature can enhance the predicative accuracy of the model using networked relationships.

For the case ID: politifact11115, all model classified the case as true, however, to improve the predictive accuracy, the proposed model identified the neighbouring news connected with the same network of the "politifact11115" node. Then, the proposed model defined influence weights and trustworthiness for each neighbouring news. The process of analysing the neighbouring news connected with the same network of the "politifact11115" node to enhances the classification. As a result, the case study "politifact11115" was corrected to fake. In addition, similar situations to the "politifact11115" news were investigated in PolitiFact "politifact11117", where the initial prediction was corrected accurately. This significantly proved the effectiveness of incorporating the "neighbouring news connected to improve fake news detection.

6. Comparison with previous graph-based deep learning model

A comprehensive comparison of our proposed SGDM-GRU method against the most recent graph deep learning models is presented in Table 9. The proposed SGDM-GRU model surpasses the performance of other baseline graph-based deep learning methods, which were evaluated using four datasets. The results in Tables 9 and 10 prove that the SGDM-GRU model was the leading model in fake news detection. First, the comparisons with baseline graph deep learning algorithms highlighted the superiority of the spectral graph deep learning approach over traditional graph deep learning approaches that rely on structural graph features. The proposed spectral graph deep learning methods showed significantly better performance, highlighting its capacity to acquire complex features from graphs, allowing the extraction of effective characteristics from user tweets.

Results highlight the proposed model's advantages of using spectral graph features to detect fake news. The proposed SGDM-GRU model, using the GRU model with the graph learning model, outperformed other graph deep learning models. This observation highlights the effectiveness of GRU in the fake news detection process compared with other approaches, such as LSTM and CNN. The integration of GRU and SGDM empowers the proposed approach to extract comprehensive high-level features of fake news, resulting in much improved fake news detection performance.

7. Recommendation

Transparency is crucial in fake news detection models. By clearly communicating the limitations and potential errors of the model to users, we help manage expectations and foster trust. Users need to understand that no model is perfect and that misclassifications can occur.

8. Conclusion and future work

In this paper, we propose an innovative model to detect fake news, the SGDM-GRU model. This model combines SGDM and GRU, significantly improving fake news detection. We evaluated the proposed model using four datasets. The obtained results show its superior proficiency in detecting fake news. Using the spectra graph deep learning technique coupled with GRU has made significant strides in fake news detection. However, there is room for improvement. In the future, we plan to integrate different DL models with SGDM to improve the proposed model's capability to identify a wide array of fake news. In addition, other datasets with different languages will be used to test the proposed model.

The developments in large language models (LLMs), such as Generative Pre-trained Transformers (GPT)-based approaches, have significantly improved the capabilities of natural language processing and provided a great potential for fake news detection issues. LLMs can explore textual context and patterns. This characteristic can be used to verify fake news sources by comparing them with trusted ones. One of our future works will be combining the LLMs with the proposed fake checking model to detect manipulative language. In addition, the challenges associated with LLMs, such as potential biases in training data, can be addressed by using diverse datasets from trusted sources that include different demographics and perspectives and also by applying sampling methods to balance datasets across classes to avoid over-representation of specific classes.

CRediT authorship contribution statement

Aqeel Sahi: Writing – original draft, Methodology. **Mostfa Albdair:** Data curation, Validation. **Mohammed Diykh:** Data curation, Writing – original draft, Software, Methodology. **Shahab Abdulla:** Writing – review & editing. **Hadi Alghayab:** Validation, Software. **Kaled Aljebur:** Conceptualization.

Declaration of competing interest

The authors declare that they have no known conflict of interest or any financial interests related to this research.

Data availability

The code and data is available at https://github.com/MOHAMMEDDIYKH/Spectral-Graph-Deep-Learning-Based-Gated-Recurrent-Unit-Model-for-Accurate-Fake-News-Detection.

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