



RESEARCH ARTICLE

Multi Linear Tensor and Graph Convoluted Attention Network Based Classifier for Fake News Detection

K. Saritha Devi^{1*}, Dr. M. Chidambaram²

Abstract

The growing acceptance of social media platforms has streamlined the news articles sharing that have induced the boom in fake news. With the appearance of fake news at a very swift rate, a pressing distress has brought out in our society due to extensive fake content propagation. The quality of the news content is uncertain and there prevails a requirement for the detection at an early stage. However detection of fake news in a swift and accurate manner is a laborious and cumbersome task. However, in terms of knowledge extraction, most existing methods lack the mining of both textual and feature knowledge hidden in the news content and discard the mutual correlation between them. To address on these gaps, in this work, a method called, Multi-linear Tensor and Graph Convoluted Attention Network-based Classifier (MT-GCANC) for fake news detection is designed. The MT-GCANC method is split into two sections, namely preprocessing, feature engineering and classification. In the preprocessing stage, Multi-linear Tensor function is applied to the raw dataset to generate computationally efficient preprocessed sample results. Second with the preprocessed sample results as input are subjected to Graph Convoluted Attention Network-based Knowledge-aware feature engineering. Here, both relevant features are extracted and then with the engineered features classification is performed for accurate and precise fake news detection. The performance of our proposed MT-GCANC method has been validated on Fake News dataset. Classification results have revealed that the proposed MT-GCANC method outperforms existing and relevant onsets for fake news detection and accomplished a precision and recall rate of 19% and 58%. These results have shown significant advancements over the existing state-of-the-art methods in the domain of fake news detection and state the probable utilization of the method for classifying fake news.

Keywords: Social Media, Multi-linear, Tensor, Graph Convoluted Attention Network, Feature Engineering.

Introduction

People are increasingly spending more time on social media due to the widespread use of smartphones, which

provide access to information anytime and anywhere, unlike conventional media. Moreover, these platforms enable interaction among friends, families, and even strangers through comments and sharing mechanisms. As a result, social media has become a predominant channel for news distribution.

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However, social media platforms also facilitate the rapid dissemination of fake news using various advanced tools and techniques. Therefore, reliable and authentic sources of information are essential to prevent the public from being misled. A multiple imputation-based method for fake news detection was proposed by Balshetwar et al. (2023), where sentiment was considered a significant feature to enhance accuracy. Initially, a lexicon-based scoring algorithm was used to identify key feature words based on sentiment analysis. Furthermore, Multiple Imputation by Chained Equations (MICE) was employed to handle multivariate missing data. In addition, Term Frequency–Inverse Document Frequency (TF-IDF) was used for feature extraction, enabling the identification of long-term weighted features. Finally, classification was performed using Naïve Bayes, Passive–Aggressive, and Deep

Neural Network (DNN) models, improving overall accuracy. However, execution time was not analyzed.

A multilingual deep learning model based on capsule networks was proposed by Mohawesh et al. (2023), incorporating multilingual embeddings and semantic features. The model employed two parallel architectures: BiLSTM for extracting contextual information and capsule networks for capturing hierarchical relationships, resulting in improved accuracy. However, execution efficiency was not considered.

Fake News Detection through News Content and Social Context (FND-NS) was introduced by Raza and Ding (2022), utilizing both news content and social context to learn meaningful representations. This transformer-based approach enabled early detection of fake news. Additionally, zero-shot learning was used to evaluate relationships between user profiles and news credibility, enhancing performance. However, classification efficiency remained a limitation.

With the rapid advancement of artificial intelligence, significant research has been conducted in fake news detection, which is considered a major threat to journalism, commerce, and democracy. A hybrid deep learning model combining Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) was proposed by Nasir et al. (2021) for classifying news as real or fake. Similarly, a BERT-based deep learning approach was introduced by Kaliyar et al. (2020), where multiple parallel convolutional blocks with different kernel sizes were used to address ambiguity and improve performance.

Despite these advancements, many existing methods rely heavily on dataset-specific feature representations and lack effective semantic modeling, limiting their ability to generalize to new data. To address this issue, a multimodal fake news detection model incorporating semantic features was proposed by Dwivedi and Wankhade (2023). This model utilized pre-trained language models to capture factual knowledge and extracted visual features to enhance semantic understanding, thereby improving accuracy.

Fake news refers to misleading or manipulated information intended to deceive readers and influence public opinion. Although its impact is significant, particularly in political contexts, relatively limited research has been conducted on AI- and machine learning-based detection methods (Akhtar et al., 2022). A hybrid deep learning model proposed by Khali et al. (2023) focused on improving classification accuracy.

However, fake news detection faces several challenges, including limited dataset availability, inefficient resource utilization, and lack of proper evaluation metrics. To address these issues, feature abstraction and vectorization techniques were applied by Dev et al. (2024), resulting in improved accuracy. Nevertheless, some methods emphasize

semantic features while neglecting content-based feature engineering.

In Samadi and Momtazi (2023), semantic-based models were developed using natural language processing techniques for fake news detection. However, these methods lacked human involvement, which is crucial for trust evaluation. To overcome this limitation, a cooperative deep learning model was proposed by Mallick et al. (2023), incorporating user feedback to evaluate trust levels and rank news accordingly, thereby improving precision and recall.

Although many existing approaches integrate textual and visual features, they often fail to capture semantic relationships effectively, leading to the loss of important information. To address this gap, an automated multimodal framework was proposed by Palani et al. (2021), combining textual and visual features with enhanced representation, resulting in improved classification accuracy.

Finally, an optimization-based approach using the Firefly algorithm combined with Multi-Support Vector Machines (MSVM) was presented by Ravish et al. (2022). This method focused on efficient feature selection and extraction, thereby enhancing overall detection accuracy.

Contributions of the work

By using Multi-linear Tensor function in combination with Graph Convolutional Attention Network-based Knowledge-aware feature engineering our proposed method works towards to design an accurate and precise method for detecting false news. The method we suggest builds upon this research by combining feature engineering and classification that can detect both textual and feature knowledge hidden in the news content, while also benefiting from the mutual correlation model that discards the irrelevant features. The inclusion of graph convolution and attention mechanism allows our method to learn increasingly complex patterns, from different authors evolve over time and also taking into consideration the mutual correlation between users (i.e., samples) first textual and feature knowledge. This can allow our method to learn increasingly complex textual patterns and hence assists in accurately representing the text's underlying structure. The overall contribution of this study includes:

- Our pioneering work, MT-GCANC, combines Multi-linear Tensor and Graph Convolutional Attention Network-based Classifier to introduce a novel method that boots the precision and robustness of identifying fake news.
- To design Multi-linear Tensor-based Preprocessing model for eliminating employing Cauchy Stress Tensor is designed. The objective is to analyze how each multi-linear subspace learning model employing Cauchy Stress Tensor enhances the ability of the model to remove redundant information and retain significant information.

- To propose Graph Convolutional Attention Network-based Knowledge-aware feature engineering model, promoting the efficient use of the learned representations via graph convolution and graph attention. This leads to precision and accurate promoting faster convergence.
- Extensive experiments were organized to inspect the influence of several performance metrics like, precision, recall, f1-measure, execution time on how well the method performs, issuing perceptions to into the application for training deep learning algorithms for detecting false news.
- Using a benchmark dataset, our suggested method reached state-of-the-art performance, manifesting the functionality of the method. Our work contributes to the increasing body of research on employing deep learning algorithms for tackling the distribution of fake news on social media.

Organization of the paper

The following is how the paper is organized. Section 2 briefs about various methods and mechanisms employed in Fake News detection using different machine learning and deep learning techniques. Section 3 explains all the algorithms and methods used during our analysis of the proposed method Multi-linear Tensor and Graph Convolutional Attention Network-based Classifier (MT-GCANC) for fake news detection. Section 4 summarizes the experimental results and its implementation details in Section 5. An in-depth analysis employing tabulator and figurative representation is provided in section 6. Finally, our study is summarized in Section 7.

Related works

The spread of false news has become a critical issue in today's information landscape, significantly influencing public opinion and decision-making processes. Efforts to mitigate this problem have led to extensive research in the application of machine learning and deep learning techniques. However, a notable gap still exists in effectively utilizing contextual cues and skip connections, which limits the development of comprehensive detection models capable of capturing complex contextual information and data distributions. To address this limitation, a deep learning model called FakeStack was proposed by Keya et al. (2023) to improve the accuracy of fake news detection. As misinformation continues to evolve in complexity, distinguishing between authentic and fake news has become increasingly challenging.

An innovative hybrid approach incorporating fuzzy logic was introduced by Xu and Kechadi (2023) to enhance fake news detection performance. This method integrates both textual and numerical contextual information, thereby significantly improving overall accuracy. Fake news

detection has emerged as a prominent research domain in recent years due to the rapid growth of social media platforms, which facilitate the widespread dissemination of misinformation. Each detection algorithm has its strengths and limitations, reflecting the dual impact of technological advancements on society.

A sentiment-based fake news detection approach was presented by Balshetwar et al. (2023), where sentiment was treated as a key feature to improve classification accuracy. In this method, multivariate missing data were handled using Multiple Imputation by Chained Equations (MICE), followed by feature extraction using Term Frequency–Inverse Document Frequency (TF-IDF). Classification was then performed using Naïve Bayes, Passive-Aggressive, and Deep Neural Network (DNN) classifiers. Additionally, a comprehensive survey of fake news detection techniques was conducted by Ali et al. (2022), while a systematic review addressing existing challenges in fake news detection models was provided by Shah and Ganatra (2022).

In the current digital era, fake news has become more prevalent and increasingly difficult to identify. Early detection remains a major challenge, particularly due to the lack of labeled datasets required for training models. A transformer-based framework for fake news detection was proposed by Raza and Ding (2022), which leveraged efficient labeling techniques to achieve high accuracy within a short time. Similarly, a transformer-based approach for detecting fake news in the Arabic language was introduced by Bou Nassif et al. (2022), utilizing contextualized embedding models to improve performance. However, timely detection remains a critical issue. To address this, Aljrees et al. (2023) integrated Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for early-stage detection.

As fake news continues to proliferate across social media, significant efforts have been made to develop automated detection systems. However, most existing methods primarily focus on linguistic and compositional features. To overcome this limitation, Park and Chai (2023) proposed a machine learning model incorporating user features, social capital, and news content using XGBoost, achieving improved prediction performance. Furthermore, Xiang (2022) developed a model that considers both textual and visual features, enhancing detection precision and accuracy.

An advanced dual-channel reasoning model based on multimodal data fusion was introduced by Ji et al. (2023), which effectively captures semantic relationships and correlations across modalities. Additionally, adaptive spatial attention mechanisms were incorporated to further improve accuracy and flexibility. A comprehensive survey on fake news classification techniques and their implementation aspects was conducted by Rohera et al. (2022), while Islam et al. (2020) provided new perspectives on misinformation

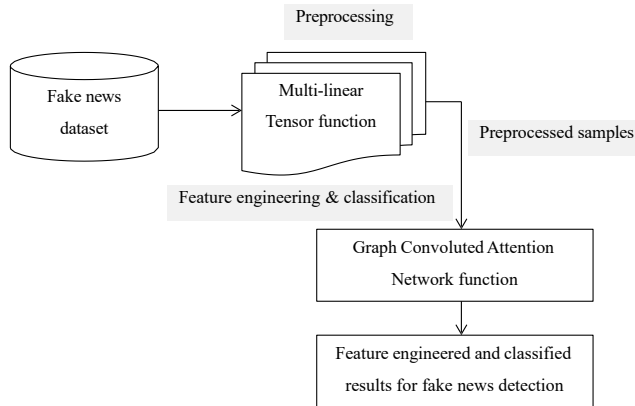


Figure 1: Block diagram of Multi-linear Tensor and Graph Convoluted Attention Network- based Classifier

detection using deep learning. To address the limitation of isolated semantic feature usage, Wu et al. (2022) proposed a multi-semantic pathway network for improved fake news detection.

An extensive review of deep learning-based techniques, including transformers, adversarial networks, and encoder-based models, was presented by Mridha et al. (2021). Despite the growing importance of fake news detection, particularly in domains such as politics and supply chain management, limited research has focused on integrating artificial intelligence and machine learning for minimizing disruptions. To address this, Akhtar et al. (2022) combined AI and ML techniques to enhance decision-making processes. Furthermore, an autonomous model based on natural language processing was proposed by Islam et al. (2021) for efficient fake news detection.

In conclusion, the development of accurate and reliable fake news detection models remains a critical research challenge. Although deep learning approaches have demonstrated promising results, further improvements are required to enhance precision and recall. One major research gap identified in existing studies is the limited integration of textual and feature-based knowledge. Fake news often relies on misleading contextual cues, which are not effectively captured by traditional methods. Another limitation is the underutilization of multi-linear subspace learning techniques, which can enhance information propagation within models. Addressing these gaps through the incorporation of multi-linear tensor-based preprocessing and graph convolutional attention networks for knowledge-aware feature engineering can significantly improve the performance of fake news detection systems. This forms the primary objective of the present study.

Methodology

In this section, a Multi-linear Tensor and Graph Convoluted Attention Network-based Classifier (MT-GCANC) method is

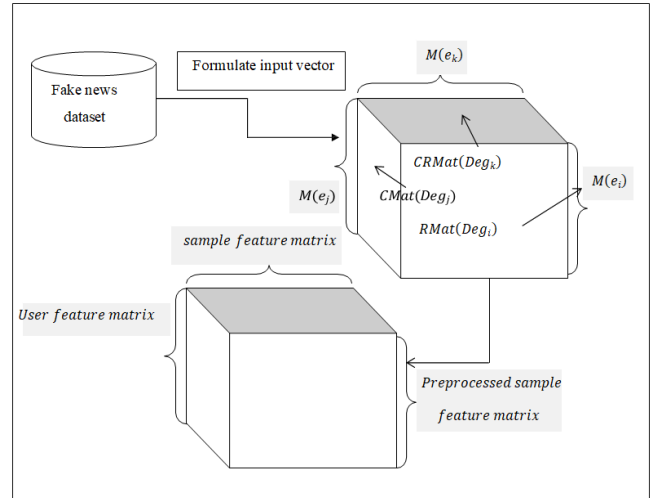


Figure 2: Block diagram of Multi-linear Tensor-based Preprocessing model

designed for fake news detection in a precise and accurate manner with minimum execution time. The MT-GCANC method is split into two sections. They are preprocessing, feature engineering and classification for fake news detection. Figure 1 given below shows the block diagram of MT-GCANC method.

As illustrated in the above figure, preprocessing is performed by means of Multi-linear Tensor function. Second feature engineering is designed by applying Graph Convoluted Attention Network-based Knowledge-aware feature engineering. Finally, with the feature engineered results, fake news detection is made using Softmax activation function. With these two processes, fake news detection is made in a computationally efficient manner. The elaborate description of the proposed MT-GCANC method is provided in the following sections.

Multi-linear Tensor-based Preprocessing model

News source text frequently carries an extensive amount of unnecessary information and this unnecessary information must be eliminated to keep possession of paramount and pertinent information to make certain that futile information will not influence the classification accuracy of the method. This procedure is referred to as text cleansing. In our work, a multi-linear subspace learning model employing Cauchy Stress Tensor called, Multi-linear Tensor-based preprocessing model is applied to eliminate unnecessary information from the raw dataset. Figure shows the block diagram of Multi-linear Tensor-based Preprocessing model.

The objective here remains in eliminating the unnecessary information. The multi-linear subspace learning model employing Cauchy Stress Tensor consists of three matrices, namely, register matrix, correlated matrix and community matrix respectively forming the second-order tensor.

User information being one of the significant information to arrive at intelligent fake news detection, for the samples 'S' obtained from dataset 'DS' the users who have forwarded these news forms the register matrix 'RMat' and the correlated matrix 'CorMat' to form the matrix sharing same data and community matrix 'CommMat' possessing same idea are subjected to multi-linear subspace learning model called, Cauchy Stress Tensor with which redundant information are removed to retain significant information without compromising the accuracy with the removal of redundant information.

The register matrix is represented by 'RMat' having the dimensions of '(m, w)', where 'm' is the total number of news articles in the dataset and 'w' is the number of words. This register matrix is employed in registering the sequences of words from the dataset 'DS'. In this correlated matrix 'CRMat', the correlated news of the user to a particular news article has been represented having the dimensions of '(m, CU)' where 'm' represents the number of samples or the total number of news articles and 'CU' denotes the correlated users sharing same data. This matrix is used to represent the counting of news articles shared by several users' on social media.

In addition a community matrix 'CMat', a user is always associated to a specific group of peoples with same liking is referred to as a user-community. The community matrix has been represented having the dimensions of '(m, Comm)' with 'm' representing the number of samples or the total number of news articles and 'Comm' denoting the detected communities for analyzing fake news. Initially, the elements of the overall matrix 'M' is initialized as given below.

$$M_{ij} = \begin{cases} \frac{1}{2m} - \frac{Deg_i Deg_j}{(2m)^2}, & \text{if } Comm_i \text{ and } Comm_j \text{ are connected} \\ 0, & \text{Otherwise} \end{cases} \quad (1)$$

From the above equation (1) the matrix 'M_{ij}' with respect to two different users 'i' and 'j' is derived based on the product of degrees of users representing similar community.

$$Deg_i = \sum_i l_i, v_i \in Comm_i \quad (2)$$

$$Deg_j = \sum_j l_j, v_j \in Comm_j \quad (3)$$

From the above equations (2) and (3) the degree of each user 'Deg_i' and 'Deg_j' is arrived at based on the vertex 'v_i, v_j' and degree vector 'l_i, l_j' respectively. Finally, the rules for fine-tuning the overall matrix 'M' with respect to connected communities that are being combined to other communities are represented mathematically as given below.

$$M'_{ik} = \begin{cases} M_{ik} + M_{jk}, & \text{if } Comm_k \text{ is connected to } Comm_i \text{ and } Comm_j \\ M_{ik} - 2 \frac{Deg_i Deg_k}{(2m)(2m)}, & \text{if } Comm_k \text{ is connected to } Comm_i \text{ but not to } Comm_j \\ M_{ik} - 2 \frac{Deg_j Deg_k}{(2m)(2m)}, & \text{if } Comm_k \text{ is connected to } Comm_j \text{ but not to } Comm_i \end{cases} \quad (4)$$

Then, with the above fine-tuned overall matrix results, the 3-mode tensor is formulated as given below.

$$T_{ijk} = PS = RMat_{ij} * Comm_{jk} \quad (5)$$

With the aid of above tensor 'T_{ijk}', the transmission of a preprocessed sample news article 'PS' in a community is represented. The pseudo code representation of Multi-linear Tensor-based Preprocessing is given below.

As given in the above algorithm with the dataset and samples provided as input the objective remains in obtaining preprocessed samples with minimal execution time. To achieve this objective, with the elements of the overall matrix initialized, the degrees of users denoting similar community is arrived at by means of multi-linear subspace learning model via Cauchy Stress

Tensor. Here, the multi-linear subspace learning model via Cauchy Stress Tensor employs the occurrence information of sentences to acquire the relationship between sentences for each user, which is abstracted by the overall matrix of the graph representation. Accordingly, a third-order co-occurrence tensor is constructed and the overall matrix is calculated based on the correlation between community decomposition of this tensor. Owing to the reason that our model takes into consideration the sentence correlation patterns, with the preprocessed samples as output, the computed representations capture more

Input: Dataset 'DS', Samples 'S = {S ₁ , S ₂ , ..., S _m }', Features 'F = {F ₁ , F ₂ , ..., F _n }'
Output: computationally efficient preprocessed sample results
Step 1: Initialize 'm', 'n' Step 2: Begin Step 3: For each Dataset 'DS' with Samples 'S' and Features 'F' Step 4: Initialize elements of the overall matrix 'M' as given in equation (1) Step 5: Formulate degrees of users representing similar community a given in equations (2) and (3) Step 6: Fine-tune the overall matrix as given in (4) Step 7: Formulate tensor as given in equation (5) Step 8: Return preprocessed samples 'PS' Step 9: End for Step 10: End

Algorithm 1: Multi-linear Tensor-based Preprocessing

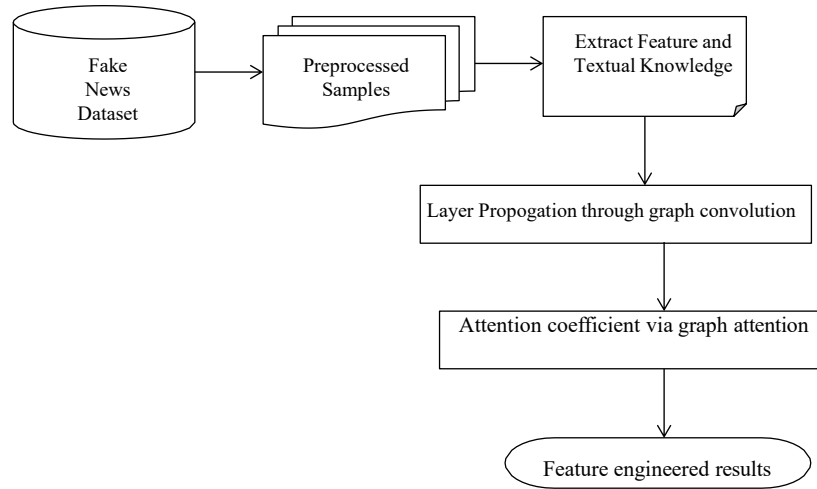


Figure 3: Block diagram of Graph Convolutional Attention Network-based Knowledge-aware feature engineering model

accurate information of news articles in a computationally efficient manner.

Graph Convolutional Attention Network-based Knowledge-aware feature engineering

Stemming from the preprocessed news text data or preprocessed samples obtained from the above section 3.1, extraneous expertise is instigated as supplementary information for fake news detection in the process of feature engineering. Owing to the reason that the fake news in many cases proliferates deceptive and inception of extraneous expertise is of positive importance for ascertaining the genuineness of news. In the interest of achieving the inception of extraneous expertise extracting textual knowledge and extracting feature knowledge evolving over time is required. In the extraneous expertise feature engineering process using Graph Convolution Network, features of every neighboring or adjacent node are collected and aggregate them with the local information for each node evolving over time. Figure 3 shows the block diagram of Graph Convolutional Attention Network-based Knowledge-aware feature engineering model.

As illustrated in the above figure, the feature engineering process is split into three sections. First, feature and textual knowledge are obtained. Second with the obtained features forms as the input to the graph convolution to form layer to layer propagation. Finally, feature engineered results are obtained by means of graph attention. The sequence of knowledge features $F = \{F_1, F_2, \dots, F_n\}$ for each news article (i.e., samples 'S') is obtained, where 'n' represents the number of features contained in each news article. The objective behind the utilization of this textual knowledge extraction is to mine words from news articles that become knowledge references for succeeding linkage in the knowledge graph. Then, the textual knowledge extraction

is mathematically represented as given below.

$$F(F_i) = \{F \mid (F \sim F_i) \in KG \in PS\} \quad (6)$$

From the above equation (6), ' $F \sim F_i$ ' represents that there exists a correlative relationship between feature ' F ' and feature ' F_i ' with ' KG ' representing knowledge graph with the knowledge entities obtained from the result of preprocessed samples ' PS ' and stored in the textual knowledge ' $F(F_i)$ ' respectively. Next, feature knowledge extraction is performed with the purpose of converting textual knowledge being extracted that cannot be perceived by computers into numerical features. Then, the feature knowledge extraction is mathematically formulated as given below.

$$F'(F_i) = W_i = \frac{1}{\text{num}(F(F_i))} \sum_{j=1}^{\text{num}(F(F_i))} F_j \quad (7)$$

From the above equation (7) the feature knowledge extraction results ' $F(F_i)$ ' are obtained based on the number of neighboring features ' $\text{num}(F(F_i))$ ' contained in ' $F(F_i)$ ', ' F ' denoting the embedding vector corresponding to ' j -th' neighboring feature in ' $F(F_i)$ ' respectively. Followed by which with the obtained textual and feature knowledge, Graph Convolutional Attention Network is employed to extract the features between different time intervals, thereby obtaining the expression of high dimension features. Initially, to obtain high dimensional features graph

convolution is formulated for each preprocessed samples. Then, the layer to layer propagation is formulated as given below.

$$H_i = \sigma(PSH_{i-1}W + b) \quad (8)$$

From the above equation (8), 'PS', 'W' and 'b' represents the preprocessed samples with the corresponding weight and bias respectively via an activation function. Then, the coefficient of attention for each layer is initially measured, in other words, for sample 'i', its similarity

coefficient with all its neighboring samples for ' $j \in m_i$ ' is mathematically represented as given below.

$$Res_{ij} = a\left(\left[W_i \parallel W_j\right]\right) \quad (9)$$

From the above equation (9) the linear mapping of the shared parameter ' W_i ' increases the dimension of sample features, laying accurate mechanism of feature extractor. On the other hand ' $\left[\cdot\right]\left[\cdot\right]$ ' join the feature of sample 'i' and sample 'j' after their conversion. Finally, ' $a(\cdot)$ ' maps high dimensional feature and hence, the learning of correlation between sample 'i' and sample 'j' is accomplished via ' W ' and ' $a(\cdot)$ ' respectively. Next, with the aid of rectified linear unit function, correlation between ' Res_{ij} ' and ' Res_{ik} ' is mathematically represented as given below.

$$a_{ij} = \frac{\exp\left(\left[LeakyReLU(Res_{ij})\right]\right)}{\sum_{k \in m_i} \exp\left(\left[LeakyReLU(Res_{ik})\right]\right)} \quad (10)$$

Finally, using the coefficient of attention and correlation between propagated samples, the extracted features are obtained as given below.

$$H_i' = \sigma\left(\sum_{j \in m_i} Res_{ij} a_{ij}\right) \quad (11)$$

From the above equation (11) results it could be concluded that the correlation between feature of samples for different

time interval as a means and employing knowledge-ware mechanism ensures accurate and precision extraction of features. After deriving the feature from graph convoluted attention network, softmax function is applied such that the fake news is eventually being detected. The formula for obtaining classified results is mathematically formulated as given below.

$$softmax(H_i) = \frac{\exp(H_i)}{\sum_{l=1}^k \exp(H_l)} \quad (12)$$

From the above equation (12), ' $\exp(\cdot)$ ' forms the exponential function with 'l' representing the total number of classes to obtain the final classification probability distribution ' $H = [H_0, H_1]$ ', where ' H_0 ' represents the target news is classified as true news and ' H_1 ' represents the target news is classified as false. The pseudo code representation of Graph Convoluted Attention Network-based Knowledge-aware feature engineered classifier is given below.

As give in the above algorithm with the objective of improving the overall precision and recall subjected to the news articles obtained from different authors differing at different time instance, Graph Convoluted Attention Network in addition to the knowledge-aware factors are taken into consideration. Owing to the reason that the information obtained from different authors evolve over time and also taking into consideration the mutual correlation between users (i.e., samples) first textual and feature knowledge were obtained. Next, the resultant information evolved over time is subjected to layer propagation forming convoluted graph structured data. Third, using coefficient of attention via rectified linear unit function, the pertinent features are extracted in an accurate and precise manner. Finally, softmax function is applied to generate the classified results with which, true news and false news are classified according to exponential function, therefore paving ways for classification in real or fake.

Input: Dataset ' DS ', Samples ' $S = \{S_1, S_2, \dots, S_m\}$ ', Features ' $F = \{F_1, F_2, \dots, F_n\}$ '
Output: accurate and precise feature engineered results
Step 1: Initialize ' m, n ', preprocessed samples ' PS ' Step 2: Begin Step 3: For each Dataset ' DS ' with preprocessed samples ' PS ' and Features ' F ' //Feature extraction Step 4: Extract textual knowledge as given in equation (6) Step 5: Extract feature knowledge as given in equation (7) Step 6: Formulate layer to layer propagation via graph convolution as given in equation (8) Step 7: Measure coefficient of attention as given in equation (9) Step 8: Measure correlation between samples using rectified linear unit function as given in equation (10) Step 9: Obtain features extraction as given in equation (11) Step 10: Return features extracted ' FE ' //Classification Step 11: Generate classified results as given in equation (12) Step 12: If ' $softmax(H_i) = H_0$ ' Step 13: Then target news is classified as true news Step 14: Else Step 15: Target news is classified as false news Step 16: End if Step 17: End for Step 18: End

Algorithm 2: Graph Convoluted Attention Network-based Knowledge-aware feature engineered classifier

Experimental setup

Experiments were conducted using the proposed Multi-linear Tensor and Graph Convolved Attention Network-based Classifier (MT-GCANC) under different learning paradigms, including multiple imputation (Balshetwar et al., 2023), multilingual deep learning (Mohawesh et al., 2023), and Fake News Detection through News Content and Social Context (FND-NS) (Raza & Ding, 2022).

The proposed model was implemented using a system configuration consisting of an Intel i5-7700K processor (4.20 GHz × 8 cores), NVIDIA TITAN GPU (12 GB × 2), 64 GB RAM (16 GB × 4), and Ubuntu 16.04 operating system. The software environment included Python 3.6 and TensorFlow-GPU 1.3.

To validate the performance of the proposed MT-GCANC model for fake news detection, several evaluation metrics were considered, including precision, recall, F1-score, and execution time. The experiments were conducted using a repeated train–test process over 10 runs, and the average values were reported to ensure reliability and consistency of the simulation results.

Implementation details

- In this study, a method called Multi-linear Tensor and Graph Convolved Attention Network-based Classifier (MT-GCANC) for fake news detection with precision, recall, accuracy and minimal execution time is designed.
- The proposed Multi-linear Tensor and Graph Convolved Attention Network-based Classifier (MT-GCANC) consists of three major stages: preprocessing, feature engineering, and classification for effective fake news detection.
- The performance of the MT-GCANC method is evaluated by comparing it with three existing approaches, namely multiple imputation (Balshetwar et al., 2023), multilingual deep learning (Mohawesh et al., 2023), and Fake News Detection through News Content and Social Context (FND-NS) (Raza & Ding, 2022), using a

benchmark fake news dataset to validate the results.

- Initially, raw data from Fake News dataset were obtained and each samples were validated and analyzed to obtain computationally efficient preprocessed sample results by formulating tensors with degrees of users representing similar community.

Second feature engineering and classification processes are carried out. Here, feature engineering process is applied to the preprocessed samples to extract both textual and feature knowledge. Next, the results obtained were subjected to coefficient of attention and correlation between samples using rectified linear unit function. Third, classified results are analyzed via convoluted graph to arrive at final target news. According to the conditional matching the samples are either found to be true news or fake news.

According to the above implementation patterns, four different evaluation metrics are discussed in the next section with the aid of table and graphical representations.

Discussion

This study uses measures of precision, recall, F1-measure, and execution time to assess the performance of the proposed MT-GCANC method and compare its efficacy. An elaborative and detailed performance analysis is discussed in this section using multiple imputation (Balshetwar et al., 2023), multilingual deep learning (Mohawesh et al., 2023), and Fake News Detection through News Content and Social Context (FND-NS) (Raza & Ding, 2022). Also, to ensure a fair comparison, the same dataset and samples are employed for all four methods: MT-GCANC, multiple imputation, multilingual deep learning, and FND-NS.

Case scenario 1: Precision analysis

Precision is computed as the ratio of correctly classified positive case and the sum of correctly and falsely classified values of the positive case. With the aid of the precision the factualness of the method is said to be analyzed.

$$Precision = \frac{TP}{TP + FP} \quad (13)$$

From the above equation (13), precision ‘Precision’ is measured taking into consideration the true positives ‘TP’ (i.e., fake news correctly identified as fake news) and false positives ‘FP’ (i.e., fake news incorrectly identified as real news), respectively. To demonstrate the efficiency of the proposed MT-GCANC method, a comparison is performed with three baseline methods—multiple imputation (Balshetwar et al., 2023), multilingual deep learning (Mohawesh et al., 2023), and Fake News Detection through News Content and Social Context (FND-NS) (Raza & Ding, 2022) [3]—based on precision under experimental conditions.

Figure 4 and Table 1 depict the precision rate with

Table 1: Precision performance comparison

Samples	Precision			
	MT-GCANC	Multiple imputation	multilingual deep learning	FND-NS
2000	0.98	0.979	0.96	0.977
4000	0.97	0.95	0.93	0.94
6000	0.95	0.93	0.9	0.92
8000	0.93	0.9	0.89	0.9
10000	0.91	0.88	0.87	0.88
12000	0.92	0.9	0.85	0.88
14000	0.94	0.91	0.85	0.86
16000	0.96	0.92	0.83	0.85
18000	0.95	0.89	0.82	0.83
20000	0.93	0.85	0.82	0.84

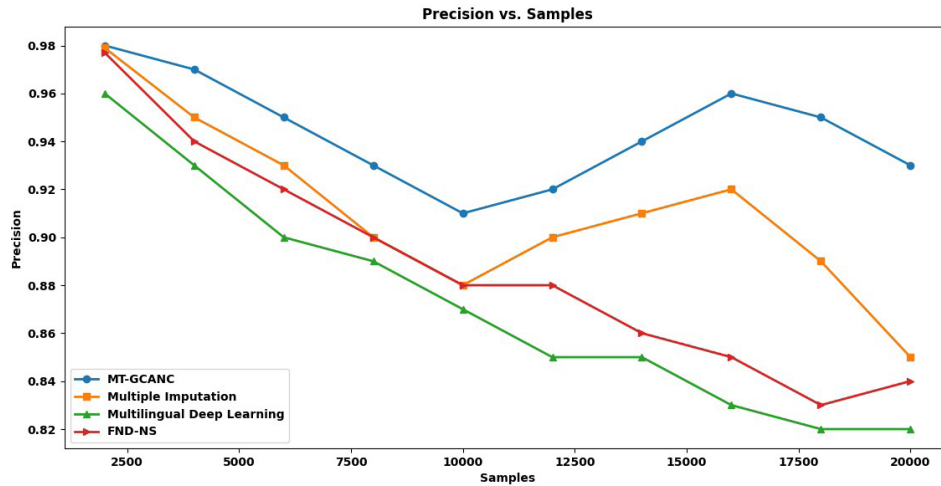


Figure 4: Comparison of MT-GCANC in terms of precision using different deep learning methods

respect to distinct numbers of samples ranging between 2000 and 20000. When taking 2000 samples as input, the precision rates of the MT-GCANC method, multiple imputation (Balshetwar et al., 2023), multilingual deep learning (Mohawesh et al., 2023), and FND-NS (Raza & Ding, 2022) were 0.98, 0.979, 0.96, and 0.977, respectively. With respect to 4000 samples, the precision rates observed in detecting fake news were 0.97 using MT-GCANC, 0.95 using multiple imputation, 0.93 using multilingual deep learning, and 0.94 using FND-NS, respectively.

In the proposed method, the Graph Convolutional Network-based Knowledge-aware feature engineering algorithm, with the preprocessed samples as input, first extracts textual and feature knowledge for further processing. In addition, propagation between layers for each preprocessed sample is achieved using graph convolution, and the coefficient of attention for each layer is measured using graph attention separately. This process reduces false positives and thereby improves the overall precision of the MT-GCANC method by 4% compared to multiple imputation (Balshetwar et al., 2023), 8% compared to multilingual deep learning (Mohawesh et al., 2023), and 7% compared to FND-NS (Raza & Ding, 2022).

Case scenario 2: Recall analysis

The recall rate is obtained by dividing the number of sample cases in which a positive case was allocated a value by the total number of sample cases in which a positive case was allocated a value and a negative case was allocated a value. With the aid of the recall rate arrived at the methods comprehensiveness is said to be provided.

$$Recall = \frac{TP}{TP + FN} \quad (14)$$

From the above equation (14), recall rate 'Recall' is measured

using the true positives 'TP' and the false negatives 'FN' (i.e., real news incorrectly classified as fake news). To demonstrate the significance of the proposed MT-GCANC method, a comparison is carried out with three baseline methods—multiple imputation (Balshetwar et al., 2023), multilingual deep learning (Mohawesh et al., 2023), and FND-NS (Raza & Ding, 2022)—based on recall under experimental conditions.

Figure 5 shows the recall performance results obtained using the proposed MT-GCANC method and three existing methods—multiple imputation (Balshetwar et al., 2023), multilingual deep learning (Mohawesh et al., 2023), and FND-NS (Raza & Ding, 2022). From the figure, samples ranging between 2000 and 20000 on the x-axis are compared with the recall rate computed using equation (14). Although a decreasing trend is observed with an increase in samples for the first six iterations, an improvement is noted in the remaining four iterations. The improvement

Table 2: Recall performance comparison

Samples	Recall			
	MT-GCANC	multiple imputation	multilingual deep learning	FND-NS
2000	0.95	0.9	0.8	0.7
4000	0.93	0.91	0.78	0.69
6000	0.91	0.89	0.75	0.67
8000	0.9	0.87	0.73	0.65
10000	0.88	0.85	0.72	0.63
12000	0.86	0.82	0.7	0.6
14000	0.88	0.8	0.75	0.63
16000	0.89	0.82	0.78	0.75
18000	0.91	0.85	0.81	0.79
20000	0.94	0.86	0.8	0.71

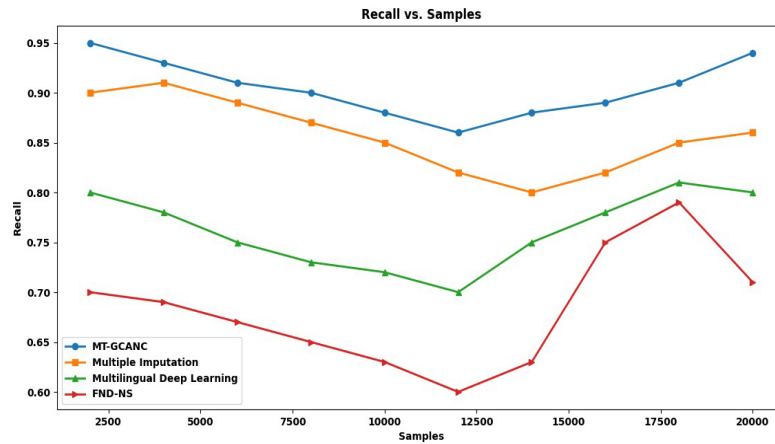


Figure 5: Comparison of MT-GCANC in terms of recall using different deep learning methods

in recall using the MT-GCANC method is attributed to the application of the Rectified Linear Unit (ReLU) function for learning correlations between samples and enabling effective mapping between high-dimensional and low-dimensional features. This, in turn, enhances the recall rate of the MT-GCANC method by 6% compared to multiple imputation (Balshetwar et al., 2023), 19% compared to multilingual deep learning (Mohawesh et al., 2023), and 33% compared to FND-NS (Raza & Ding, 2022), respectively.

Case scenario 3: F1-measure analysis

The F1 score measures the execution of the method for each case. F1-score is utilized in case of the unbalanced data. As an assessment, the F1-score performance metric is utilized in demonstrating the fullness of the recommended method in terms of class-wise accuracy.

$$F1 - score = 2 \frac{Precision * Recall}{Precision + Recall} \tag{15}$$

Table 3: F1-score performance comparison

Samples	F1-score			
	MT-GCANC	multiple imputation	multilingual deep learning	FND-NS
2000	0.964767	0.937839	0.872727	0.815623
4000	0.949579	0.92957	0.848421	0.795828
6000	0.92957	0.90956	0.818182	0.775346
8000	0.914754	0.884746	0.802099	0.754839
10000	0.894749	0.86474	0.787925	0.734305
12000	0.888989	0.85814	0.767742	0.713514
14000	0.909011	0.851462	0.796875	0.727248
16000	0.923676	0.867126	0.804224	0.796875
18000	0.92957	0.86954	0.814969	0.809506
20000	0.934973	0.854971	0.809877	0.769548

From the above equation (15), the F1-score result ‘F1-score’ is obtained based on the precision ‘Precision’ and recall rate ‘Recall’. To demonstrate the efficiency of the proposed MT-GCANC method, a comparison is carried out with three baseline methods—multiple imputation (Balshetwar et al., 2023), multilingual deep learning (Mohawesh et al., 2023), and FND-NS (Raza & Ding, 2022)—in terms of F1-score for distinct numbers of samples, as presented in Table 3.

Table 3 and Figure 6 show the performance of the MT-GCANC method and the existing methods—multiple imputation (Balshetwar et al., 2023), multilingual deep learning (Mohawesh et al., 2023), and FND-NS (Raza & Ding, 2022)—in terms of F1-score. As far as statistical analysis is concerned for binary classification (i.e., fake news or true news), the F1-score is a measure of predictive performance. It is evaluated from the precision and recall of the fake news detection test, where precision refers to the number of true positive results divided by the number of all samples predicted to be positive, and recall refers to the number of true positive results divided by the number of all samples that should have been identified as positive. Hence, the F1-score is the harmonic mean of precision and recall, thereby representing both metrics in a single measure. From the above analysis, the F1-score obtained using the MT-GCANC method is found to be comparatively better than multiple imputation (Balshetwar et al., 2023), multilingual deep learning (Mohawesh et al., 2023), and FND-NS (Raza & Ding, 2022). This improvement is achieved by applying the Graph Convoluted Attention Network-based Knowledge-aware feature engineered classifier algorithm. Since user information changes over time due to preferences, likes, and dislikes, mutual correlations between users are leveraged to extract both textual and feature knowledge. Subsequently, layer propagation is performed using a convoluted graph structure, followed by the use of attention coefficients computed through the Rectified Linear Unit (ReLU) function to extract relevant features. Finally, classification into real or fake news is performed using the softmax function based on

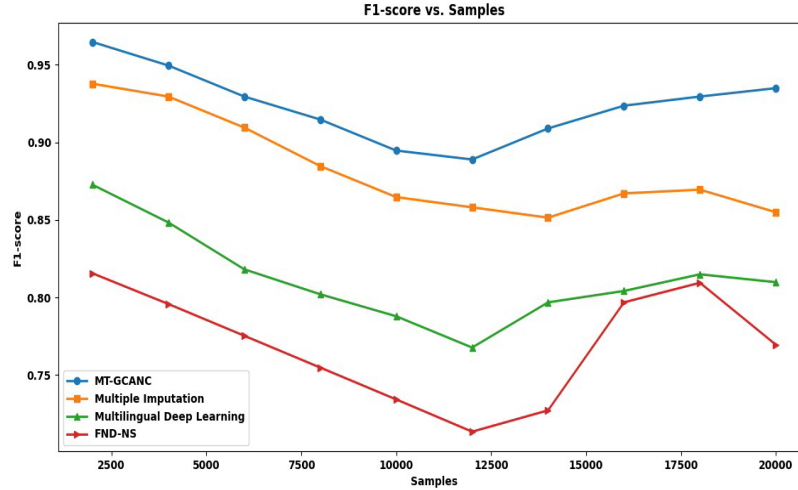


Figure 6: Comparison of MT-GCANC in terms of F1-score using different deep learning methods

the exponential function, thereby improving precision and recall, which in turn enhances the overall F1-score.

Case scenario 4: Execution time analysis

Finally, in this section the execution time or the time consumed in obtaining the relevant features is measured as given below.

$$ET = \sum_{i=1}^n S_i * Time [f(v_i[FE])] \tag{16}$$

From the above equation (16), the execution time 'ET', is measured by taking into consideration the samples taken for simulation 'S_i' and the time consumed in extracting the relevant features 'Time [f(v_i[FE])]' for detecting fake news. It is measured in terms of milliseconds (ms). Finally, in Table 4, the significance of the proposed MT-GCANC method is evaluated by comparing it with three baseline methods—multiple imputation (Balshetwar et al., 2023), multilingual deep learning (Mohawesh et al., 2023), and FND-NS (Raza & Ding, 2022)—under experimental conditions in terms of execution time.

Table 4: Execution time performance comparison

Samples	Execution time (ms)			
	MT-GCANC	multiple imputation	multilingual deep learning	FND-NS
2000	220	260	300	360
4000	255	285	335	365
6000	315	335	355	390
8000	335	350	385	405
10000	350	395	415	430
12000	385	415	465	485
14000	415	445	500	525
16000	435	485	535	585
18000	485	510	585	615
20000	500	535	615	635

Finally, the execution time performance results of the four methods—MT-GCANC, multiple imputation (Balshetwar et al., 2023), multilingual deep learning (Mohawesh et al., 2023), and FND-NS (Raza & Ding, 2022)—are illustrated in



Figure 7: Comparison of MT-GCANC in terms of execution time using different deep learning methods

Figure 7. According to the results, as the number of samples increases, the test execution time also increases. This indicates that the Multi-linear Tensor function processes more information due to the inclusion of additional features. However, after selecting the most relevant features, the inclusion of optimal features enhances the method's performance and improves the overall execution time of the MT-GCANC method compared to the baseline methods. This demonstrates that the application of the Cauchy Stress Tensor in the MT-GCANC method effectively removes redundant information while retaining relevant samples for further processing. Additionally, the use of three different matrices in the Multi-linear Tensor enables preprocessing to be performed separately for registration, correlation, and community representation. As a result, the MT-GCANC method reduces execution time by 8% compared to multiple imputation (Balshetwar et al., 2023), 18% compared to multilingual deep learning (Mohawesh et al., 2023), and 23% compared to FND-NS (Raza & Ding, 2022), respectively.

Conclusion

While social media provides ease of news propagation, it also leads to the widespread dissemination of fake news. Effective detection of fake news is essential for creating a healthy network environment and ensuring societal security. In this work, a methodology based on a Multi-linear Tensor-based preprocessing model and a Graph Convoluted Attention Network-based Knowledge-aware feature engineering model is presented. For early fake news detection, a Cauchy Stress Tensor is introduced through a multi-linear subspace learning model. Subsequently, both feature and textual knowledge are extracted, along with layer-wise propagation using graph convolution and attention coefficients computed via graph attention. The performance of the proposed method is evaluated using a real-world fake news dataset. Simulation results demonstrate that, compared to multiple imputation (Balshetwar et al., 2023), multilingual deep learning (Mohawesh et al., 2023), and FND-NS (Raza & Ding, 2022), the proposed approach significantly improves performance in terms of precision, recall, F1-score, and overall execution time.

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