



Residual Graph Convolutional Networks for Improving Rumor Detection from Social Media Texts

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Abstract

Internet and social media have become significant platforms for sharing real-time information, with rumors significantly affecting billions of people's perceptions. Considerably, Rumor recognition is the most challenging task on social media platforms. Numerous Deep Learning (DL) models have been developed to extract linguistic characteristics from short-text tweets for rumor prediction. However, these models struggle to capture the intricate spatiotemporal relationships presenting tweet interactions. To address this issue, Bidirectional Encoder Representation from Transformers with Attention based Balanced Spatial-Temporal Graph Convolutional Networks (BERT-ABSTGCN) was used. This model incorporates Spatial-Temporal Attention Mechanism (STAM) and a Spatial-Temporal Convolution Module (STCM) to effectively model the spatiotemporal dependencies within in tweet interactions to enhance rumor detection. However, it constitutes to high degradation problem due to convergence issues. A popular solution to these problems is Residual Learning (RL), which introduces identity mappings to speed up training and enhance gradient propagation. However, traditional RL can only be used for layer-wise task refining, which severely restricts its capacity to grasp more generalized dependencies. However, conventional RL is restricted to layer-wise refinement within a single task limiting its ability to capture broader dependencies. To address this, the proposed work is included with a Cross-Residual Learning (CRL) in BERT-ABSTGCN named BERT with Attention-based Balanced Spatial-Temporal Residual Graph Convolutional Networks (BERT-ABSTRGCN) for efficient rumor detection and stance classification. CRL of BERT-ABSTRGCN enable intuitive learning across multiple tasks like rumor detection and stance classification using cross-connections. CRL establishes direct connections between shallow and deep feature representations, mitigating the vanishing gradient issue. The fitted residual mappings in the CRL will facilitate the BERT- BERT-ABSTRGCN with the provided information by using the short cut connections and lowers the probability of model degradation. BERT-ABSTRGCN effectively identifies rumor with different stances about specific social media posts, thereby preventing the spread of rumors. Experimental evaluations show that BERT-ABSTRGCN achieves 95.62% accuracy on the PHEME dataset and 90.15% on Mendeley's COVID-19 rumor dataset, significantly surpassing traditional models.

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1. Introduction

The Internet of Things (IoT) connects billions of devices and sensors enabling continuous data exchange and real-time analysis [1]. When integrated with social media platforms, this paradigm evolves into the Social Internet of

Things (SIoT) [2] that interconnects the devices to not only share sensor data but also interact with Online Social Networks (OSN) platforms like Facebook, Twitter, Weibo and WeChat. These OSN platforms captures massive volumes of user-generated contents like Instagram, twitter, posts and comments that can be processed within SIoT systems to monitor public discourse in real time and triggers rapid alerts in on time [3].

Rumors are a prevalent form of misinformation that spread rapidly and widely, often causing significant harm to individuals and communities [4]. This highlights the growing concern of rumors on OSNs as a serious social issue [5]. In contrast, relying on manual methods to identify and filter rumors with average accuracy is unrealistic and insufficient. In mean time, people have focused towards stances that refer to their attitude or position towards a rumor or piece of information, which can range from believing it to doubting its authenticity, to dismissing it as false, depending on their perspective or viewpoint [6]. Understanding user responses to rumors offers valuable insights, as certain denying or questioning voices can help identify false information. Stance classification is the process of determining the writer's position on a particular topic or issue. This task involves examining written content, and at times, the user's interactions on discussion forums or social media platforms [7].

Comment involves a response that does not explicitly support or deny the rumor but offers an observation or opinion related to be referred as stance [8, 9]. For instances, rumor veracity is influenced by support and deny, with queries potentially indicating the rumor's untruthfulness. Rumor identification with stance attitude categorization is a complicated process, which is connected to many elements of characteristics, including content, user, and propagation and so on. Various researches have been developed to detect both rumor and stance classification from social media data. The global structural qualities between the original tweet and its responses are underutilized, and learning becomes more complex due to the content and local structural attributes.

Recently, DL model are adaptively applied to solve the above-mentioned issues for efficient and automatic rumor detection [10]. DL models are capable of extracting linguistic features, temporal-social cues and both micro and macro level structural patterns from original tweets and their corresponding replies for rumor detection [11]. Deep Feature Fusion for Rumor Detection (DFFRD) [12] was developed for efficient rumor prediction on Twitter. The features of short-text tweets and the temporal-structural information from proliferation trees are both accounted for in this model. Nevertheless, the sparse, imperfect, and high-dimensional spatiotemporal relationships are not captured by this approach.

BERT-ABSTGCN model is proposed to effectively identify rumors by learning the spatiotemporal relationships in twitter exchanges. Using a BERT-based source tweet representation, this model extracts linguistic traits that rely on context from the dataset. Two modules, such as STAM and convolution, make up the model. ABSTGCN enhances the performance of Attention-based Spatial-Temporal Graph Convolutional Networks (ASTGCN) by modifying them to handle irregular graph connections. However, this ABSTGCN model encounters convergent problems, which causes a degradation problem. These issues can be mitigated by RL mechanism by introducing by introducing identity mappings, which enhance gradient propagation and accelerate convergence. However, standard RL remains confined to layer-wise refinements, restricting its scope to local optimizations.

For this reason, BERT-ABSTRGCN is developed to eliminate the degradation problem due to convergence of ABSTGCN for rumor detection with stance classifications. In this method, CRL is used in the BERT-ABSTRGCN to prompt the intuitive learning across multiple tasks like rumor detection and stance classification using cross-connections. By overlaying the identity mapping operation over a network, CRL solves the vanishing incline issue and instantly links the low to high-level interpretations. This identity map in RL uses the short-cut interactions to learn the essential mapping and adjusting those maps by various stacked layer to increases the network profundity. The in-network regularization that accomplishes these cross-residues allows for a more generalizable network. The fitted residual mappings in the CRL will facilitate the BERT-ABSTRGCN with the provided information by using the short cut connections and lowers the probability of model degradation. This model effectively discerns different stances about specific posts on social media and provides essential steps to prevent rumors from spreading.

The structure of the paper is as follows: Section II reviews recent rumor detection models proposed by various authors. In Section III, the BERT-ABSTRGCN model is introduced, followed by an evaluation of its performance in Section IV. Finally, Section V concludes the study and outlines potential future research directions.

2. Related Work

Zojaji & Tork [13] developed an Attentive Cost-Sensitive Loss Function (ACSLF) for rumor-stance classification. The AdCost operation was used to dynamically modify the cost matrix values using the distribution of performance

across different classes. Deep Neural Network (DNN) model was combined with the Cost-Sensitive Cross-Entropy (CSCE) loss function to enhance the infrequent class's detection in rumor categorization. However, their approach did not focus on improving the models' capacity to extract meaningful patterns from the limited and unstable data. Roy et al. [14] constructed a Sorted, Non-intersecting, and Completely Exhaustive (SeNoCe) feature space generation model for Twitter rumor stance veracity categorization. The model uses orthogonality constraints to distinguish rumor veracity and detect stance overlap and provides detailed extraction of implicit features for accurate classification. However, it cannot efficiently capture the long-term temporal features resulting in less accuracy.

Cui & Shang [15] presented a Knowledge based Attention Integrated Graph Network (KAGN) for social media rumor detection. This model uses Graph Neural Networks (GNNs) to recognize the entity mentions in posts and connecting them to relevant concepts within knowledge graphs, incorporating contextual knowledge into text representations. However, this approach was limited in its ability to assess the credibility of news when the text lacks explicit entities. Chen et al. [16] developed a Topic and Structure based Neural Network (TSNN) to predict rumors. The model predicts rumors using coarse-grained and fine-grained topic signals, with a new task leveraging royal topic information in source posts. It uses a multi-task learning approach to predict topic and user credibility. Nevertheless, the model was influenced by excessive noise, which hinders the performance enhancement.

Bai et al. [17] introduced a Multi-task Attention Tree Neural Network (MATNN) for classifying stances and detecting rumor authenticity. The approach uses Regular Rumor Conversation Trees (RC-Trees) to model rumor discussions, converting irregular structures into standardized RC-Trees. The Tree Self-Attention mechanism captures local patterns to assess rumors' credibility. However, the model's extensive number of training parameters makes it time-consuming to refine the rumour dataset. Alturayef et al. [18] developed a Multi-Task Learning (MTL) model for stance detection, integrating both Parallel MTL (PMTL) and Sequential MTL (SMTL) approaches. These methods effectively identify the relationships between sentiment, stance and sarcasm in textual analysis. However, it has a high level of complexity to adjust the parameters because there are more learning variables.

Feng et al. [19] proposed a bi-directional multi-level graph contrastive learning (BiMGCL) framework for detecting rumors. The technique uses bi-directional graph to model rumor diffusion, generating positive and negative sample pairs for multi-level contrastive learning, which evaluates representation consistency to enable rumor prediction. Nevertheless, the model generalizability was poor since the reported dataset cannot be evaluated with the number of data on the large network. Zhu et al. [20] proposed a rumor identification method that integrates semantic attributes, positional data, and user-profile weights, where a pre-trained model extracts stance information from comments, a Cross-model Transformer captures temporal features with post context, and a multi-layer perceptron performs final rumor categorization. However, this technique excels mainly in managing events with extended time dependencies.

Li et al. [21] presented a Few-Shot Fuzzy Rumor Detection (FSRD) model with query learning of stance of rumors. A fuzzy logic-based rumor detection system was developed using prompt learning to generate comment templates, augmenting source rumor data. A zero-shot learning method was suggested for identifying source rumors by capturing template features. However, accuracy was less because it could not learn the temporal patterns of rumor dissemination. Luo et al. [22] devised an integrated rumor and stance detection using semantic and structural information in social networks. The Graph Transformer Network (GTN) was utilized for intuitive rumor verification, while contrastive learning optimized semantic space representation, and the Partition Filter Network (PFN) modeled rumor detection and stance classification tasks. However, it has low accuracy since more important features were not considered, resulting in less credibility. Ma et al. [23] developed a Dual Stance-aware Multi-Task Model (DSMM) for rumors veracity on OSNs. The model uses a position-sensitive semantic adjustment method, directed attention network, and cross-attention mechanism to address semantic variations in claim semantics and local stance relevance. However, it needs advanced attention strategy to learn temporal features for increasing the detection accuracy.

The limitations of above models are overcome by proposed BERT-ABSTRGCN addresses these gaps by combining BERT for rich contextual text features and ABSTRGCN capture complex interaction patterns. The integration of CRL enables effective cross-task feature sharing, mitigating vanishing gradients and improving multitask stability. This design enhances both temporal modeling and reducing performance degradation in deeper architectures, which provides effective rumor detection and stance classification.

3. Proposed Methodology

The overall workflow the suggested model is shown in Figure (1).

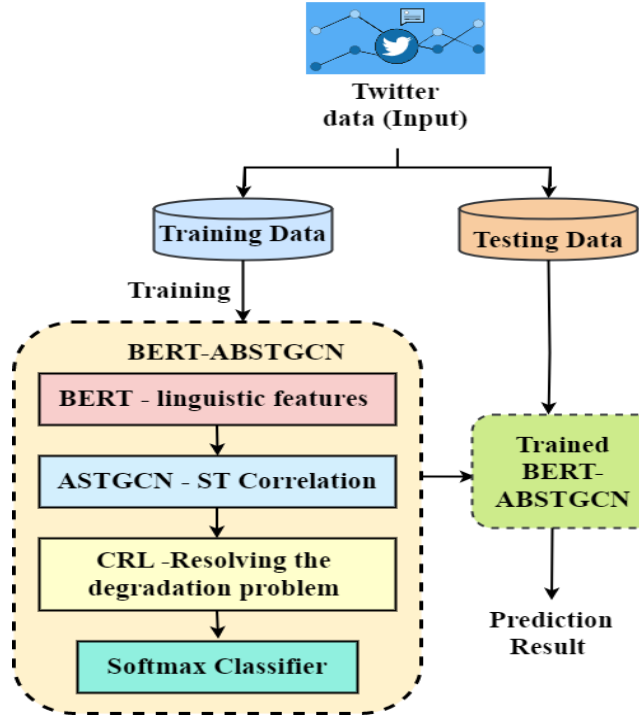


Figure 1. Pipeline of the Proposed Model

3.1 Handling complex Spatio-Temporal (ST) Dependencies in Tweet Interactions

In this model, BERT based source tweet interpretation is employed to capture context sensitive linguistic features from the tweet text, while ABSTGCN leverages STAM to model intricate spatial relationships and dynamic temporal dependencies. The STCM module captures spatial features from the graph-based twitter interaction network and temporal convolutions to represent neighborhood time slices. To reduce the network depth, the generated features from BERT and ABSTGCN within BERT-ABSTGCN frameworks are provided as inputs to the CRL model to perform the rumor stance prediction and classification.

3.2. Cross Residual Learning

RL was introduced in ResNet; uses shortcut connections to bypass one or more layers, helping deep networks mitigate vanishing gradients and improve convergence. However, in ResNet-style RL, these shortcuts operate only within a single task, limiting feature refinement to isolated task branches and preventing cross-task knowledge sharing. CRL extends RL by introducing cross-task connections that enable features from one task to be shared and refined in another, allowing richer information flow across the network. Unlike standard RL, CRL lets low-level features from one task enhance high-level representations of another, thereby improving stability, reducing performance degradation, and boosting multitask learning efficiency. This cross-task feature sharing makes CRL particularly effective for complex problems such as simultaneous rumor detection and stance classification, and is applied here to address the convergence issues in BERT-ABSTGCN.

To address convergence issues in BERT-ABSTGCN, consider an input vector a and output vector b fed into the RL layer. The mapping function $\mathcal{F}(a, \{w_x\})$ is applied to adjust the model's behavior. For example, this involves a series of convolutional operations with batch regularization followed by Rectified Linear Unit (ReLU) activation. The RL formulation is expressed in Eq. (1),

$$b = \mathcal{F}(a, \{w_x\}) + w_g a \tag{1}$$

Where, \mathbf{w}_x defines the possible vertical extension but paring dimensions with the short-route interactions. In the frame of identity short-route communications $w_g = 1$. The simple and effective elongation of RL i.e., CRL. In a given task T and other related task $n - 1$, the output generated by the cross-residual module is described as follows,

$$b^T = \mathcal{F}(a, \{\mathbf{w}_x^T\}) + \sum_{v=1}^N \mathbf{w}_g^{(v)} \quad (2)$$

In Eq. (2), the superscript (\cdot) represents the target task index, with the normalization factor omitted for straightforward tasks and incorporated into the short-path weights $\mathbf{w}_g^{(v)}$. Additional tasks contribute additively to the current target task T through the sum $\sum_{v \neq T} \mathbf{w}_g^{(v)} a$. Cross-residual enhancements generally consist of operational stacks represented by $\mathcal{C}(a, \{\mathbf{w}_{g,z}^{(v)}\})$. However, in this scenario, a simplified weighting is denoted as $\mathbf{w}_g^{(v)} a$.

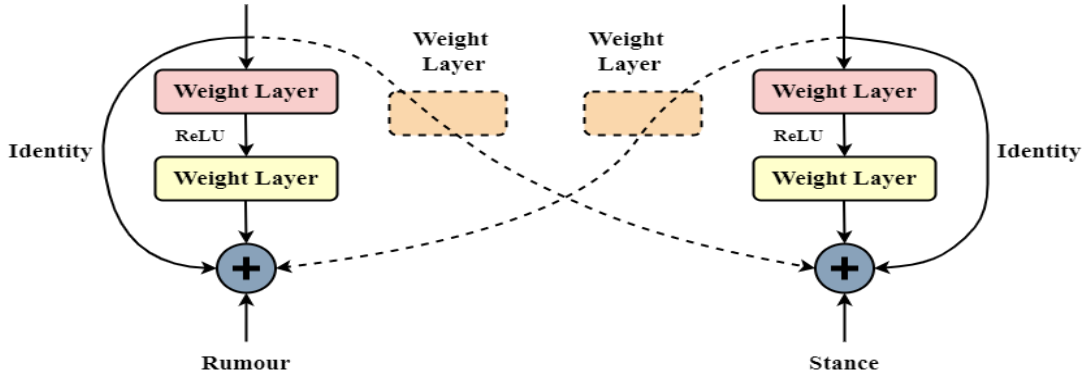


Figure 2. Cross-Connection Blocks with Two Tasks (Rumor and Stance)

Figure (2) illustrates the Cross-Connection Block incorporates weight layers and skip pathways (dotted lines) that provide flexibility within the network, enabling tailored adjustments for specific tasks. The traditional RL uses only intra-task shortcuts; CRL incorporates cross-task shortcuts allowing low-level features from one task to directly influence another. This provides enriched information flow improves generalization, stabilizes training in multitask settings and reduces the risk of performance degradation in deeper architectures.

3.3 Optimized Regularization Strategy

In optimization, the goal is to reduce the loss function $\mathcal{L}(f(a), b)$ while managing model complexity through regularization, which helps to control overfitting. In BERT-ABSTGCN, a squared 222-norm approach is applied to limit large parameter values; thereby smoothing the network's mapping functions. Cross-residual units enhance stability by aligning the primary task's solutions with those of similar tasks, ensuring that the derived mapping $\mathcal{F}(a, \{\mathbf{w}_x^T\})$ stays close to a weighted composition of task-specific transformations $\sum_b \mathbf{w}_g^{(v)} a$. This design ensures that mappings effectively address OSN feature recognition for rumor and stance detection without deviating from relevant patterns.

While traditional BERT-ABSTGCN regularization typically occurs in the loss layer, integrating cross-residual layers allows for earlier conditioning within the network, facilitating layer-to-layer information flow. These layers focus on task-specific adjustments rather than solely relying on end-stage regularization, thus introducing a form of in-network regularization earlier in the architecture that operates similarly to dropout but with reduced unpredictability. Because of the CRL, these dropouts do not affect BERT-ABSTRGCN model and cross learning model improves the learning of multi-tasking features (rumor and stance) effectively.

3.4 Integration with Highway Network

RL can be characterized as direct networks that lack modifications or transfer gates. In these networks, the final processing layer is formulated as follows:

$$b = \mathcal{H}(a, \mathbf{w}_h) \mathcal{J}(a, \mathbf{w}_T) + a. \mathcal{C}(a, \mathbf{w}_C) \quad (3)$$

In Eq. (3), \mathcal{J} and \mathcal{C} represent the transfer and carry gates, respectively. The two gates operate in a manner similar to a residual layer's. It is also possible to include a cross-residual layer with several paths into a common data channel. Cross-residual weighted layers act as carry gates, determining the degree of cross-task integration. A Feed

Forward Long Short-Term Memory (FFLSTM) network as shown in Eq. (4), is another possible way to think about residual layers.

$$\begin{aligned}
i_t &= \sigma(W_{ai}a_t + W_{hi}h_{t-1} + b_i) \\
f_t &= \sigma(W_{af}a_t + W_{hf}h_{t-1} + b_f) \\
c_t &= f_t c_{t-1} + i_t \tanh(W_{ac}a_t + W_{hc}h_{t-1} + b_c) \\
o_t &= \sigma(W_{ao}a_t + W_{ho}h_{t-1} + b_o) \\
h_t &= o_t \tanh c_t
\end{aligned} \tag{4}$$

In this formulation, t represents the current time step, and i , f and o denote the input, forget, and output gates, respectively. A cell state c and output state h will be updated during the process. To simplify, peephole connections and bias terms are excluded. In the feed-forward scenario, the recurrent connection $t - 1$ is disregarded, and the FFLSTM is treated as ungated, i.e., $i = f = o = 1$, with the initial cell state $c_{t-1} = a$, resulting in a residual-like structure. With this modification, the cross-connection layers like an ungated FFLSTM with additive cell state combining. LSTM forget gates are similar to cross-residual weight layers. Here, the FFLSTM lacks the transfer gate and instead consist only of forget gates. To enable more detailed connections, cross-connection layers are link to change the input \mathcal{H} to other prior cell states $c_{t-1}^{(v)}$ or information pathways $a^{(v)}$, fostering interconnections that are more complex.

3.5 Multi-Task Cross Residual Network (MT-CRN)

Introducing a branching point in a network enlarges the input feature map for each separate network head, which can lead to higher memory demands in multitask networks. Deeper layer branching limits representational specialization for every activity to a smaller set of high-level conceptual characteristics. Within the structure of MT-CRN (X-ResNet), the above-mentioned issues are resolved through letting in an extra cross-task integrated through the cross-residual weights that simply enhances the late layer depicting the energy having no need for large input feature spaces. The network architecture may be reduced by eliminating a crossing point and connecting many network poles via cross-residual skip connections, however this outputted as a memory-intensive compound system that is only possible in multi-GPU systems (The problem might be solved by employing frozen weights in combination with greedy layer-wise retraining). Additionally, to incorporate task specialization, final ReLU activation and batch normalization is transferred within the residual building block and away from the branching point in multitask network architecture, following the element-wise addition for each task.

The technique of adjusting normalization at each task branch increases performance marginally in multifunctional networks with branching points, since the overall network loss is the sum of distinct network head losses. Despite adjusting the loss weight for each individual branch, the overall loss across all network nodes is computed without using any weights. When all cross-connection weights are uniform, each job contributes equitably, which usually leads to a large decline in the efficiency of the multitask network. When tasks overlap cross-residual weights, it becomes difficult for a particular task to focus on learning useful selective characteristics that are separate from each other. It is reasonable to assume that making cross-residual weights zero $W_g^{(b)} = 0, \forall g \neq v$, equivalent to a multitask network, enables greater task specialization and delivers optimal discriminative performance, even when tasks are required to share equal weights across all of them. By utilizing the CRL, the converging issues in the ABSTGCN model will be resolved to predict the rumour and stance. The below mentioned Figure (3) and algorithm provides the overall structure of the suggested model. The STGCN structure and CRL learnings are depicted briefly. $W_g^{(b)}$ is updated among rumor and stance for feature sharing of one another. The updated weight accurately identify the rumor and stance.

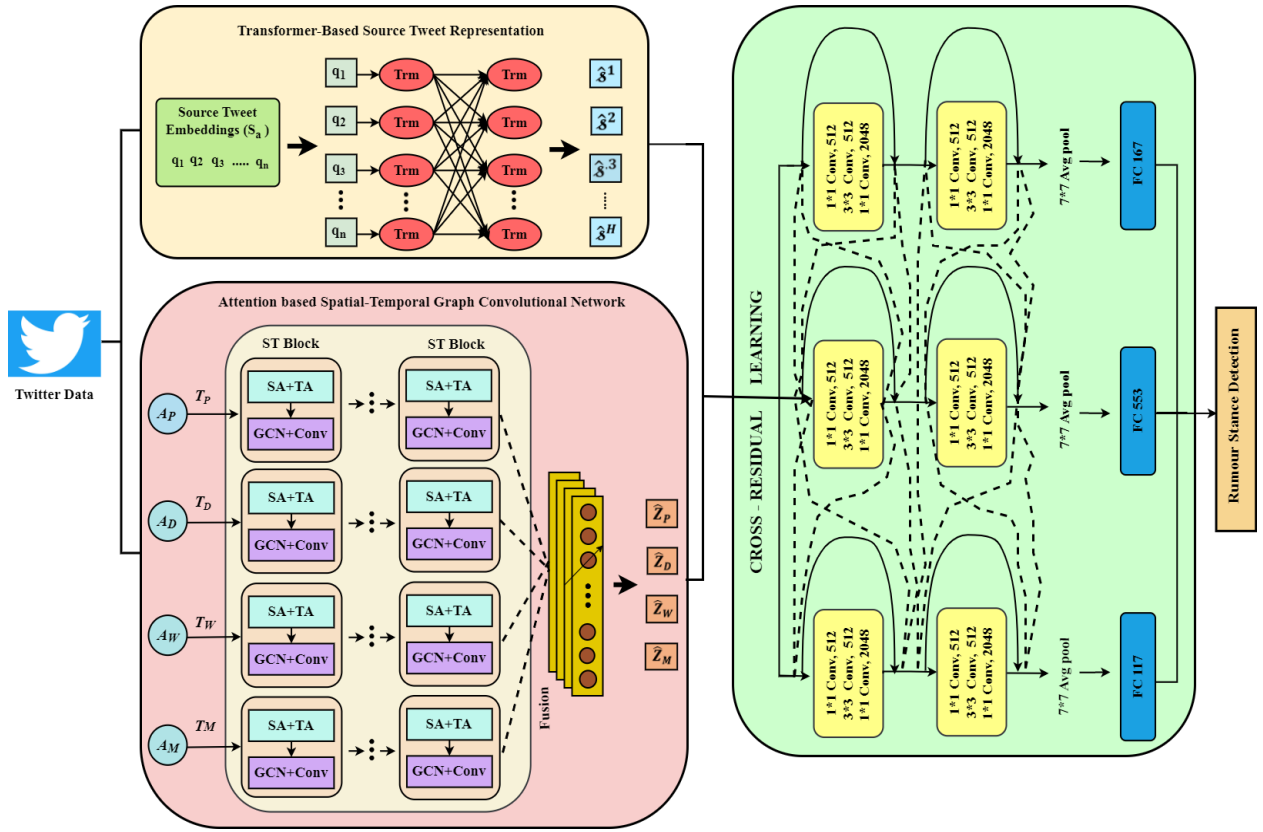


Figure 3. Complete Framework of proposed BERT-ABSTRGCN model

Algorithm: Proposed BERT-ABSTRGCN for rumor prediction

Input: Twitter Dataset – Tweets

Output: Rumor Stance Detection and classification

- Step 1:** Divide the collected tweet dataset is divided into training and testing sets.
- Step 2:** Apply BERT model to extract language traits that are sensitive to context from the actual tweet context.
- Step 3:** Develop an ASTGCN model to capture intricate spatiotemporal relationships within tweet interactions.
- Step 4:** Decompose the ASTGCN into a STAM component and STCM module.
- Step 5:** Employ the STAM to model intricate spatial and temporal dependencies.
- Step 6:** Identify the nearest time dependences form tweets using temporal convolutions.
- Step 7:** Devise STCM to retrieve the temporal and geographical relationships contained in the source tweet representations.
- Step 8:** Deploy the graph convolutions to examine adjacent time segments of tweets for spatial and temporal features estimations.
- Step 9:** Modify the dimensions of spatial and temporal adjacency matrices for ABSTRGCN.
- Step 10:** Extract the features from BERT and ABSTRGCN.
- Step 11:** Concatenate the features and fed into the CRL model to eliminate the convergence issues.
- Step 12:** Design the CRL as different many highways converging into a shared information pathway for predicting rumor stance.
- Step 13:** Train the LSTM by the Rectified Linear Unit (ReLU) activation to get the trained model.
- Step 14:** Test the data using the trained LSTM model to estimate the desired target.
- Step 15:** Evaluate the efficiency of prediction.
- Step 16:** End.

4. Result and Discussion

4.1 Dataset Description

For the purpose of this experiment, the PHEME dataset [24] is used for rumor detection and truthfulness classification. This dataset includes a set of Twitter posts containing both rumors and non-rumors during major news events. It covers rumors linked to 9 distinct events, with each rumor labeled for its truthfulness: true, false, or uncertain. In this dataset, PHEME dataset was transformed into CSV format, with emphasis placed on two events: the German wings crash and the Charlie Hebdo incident. The dataset comprises over 60,000 entries, from which 62,446 tweets were selected. Of these, 70% (43,712) were used for training, while the remaining 30% (18,734) were reserved for testing.

Mendeley’s COVID-19 Rumor Dataset [25]: It contains 4612 tweets collected between February 12 and June 15, 2020, using COVID-19–related keywords. Each tweet is labeled as rumor or non-rumor (with 485 tweets marked as rumors, about 11% of the data based on verification from credible sources like BBC News and Reuters. The dataset includes tweet text, posting date, and metadata such as retweet count and likes. It focuses exclusively on Twitter posts in English, making it ideal for social media based rumor detection.

4.2 Performance Analysis Metrics and Parameter Settings

This section explains the BERT-ABSTRGCN model's effectiveness in comparison to existing rumor stance detection algorithms such as DFFRD [12], ACSLF [13], SeNoCe [14], MATNN [17], FSRD [21] and DSMM [23]. The considered dataset is described in Section 4.1. The proposed and existing models are implemented in Python 3.11. The system used for the tests is a 64-bit version of Windows 10 with an Intel® Core™ i5-4210 CPU running at 3GHz, 4GB of RAM, and a 1TB HDD. The performance measures that were utilized to compare the proposed and existing algorithms are given below. Similarly, in Mendeley’s COVID-19 rumor dataset, 4612 tweets have been considered in which 70% (3228) are taken for training and 30% (1384) considered for testing. Table (1) depicts the hyperparameter settings of proposed and existing models.

Table 1: Hyperparameter Settings

Models	Parameters	Range
DFFRD[12]	Learning rate	0.1
	Epochs	120
	Batch size	32
	Dropout rate	0.9
	Activation Function	ReLU
	Optimizer	Adam
ACSLF [13]	Epochs	80
	Learning Rate	0.001
	Batch size	64
	Activation Function	Tanh
	Optimizer	AdaGrad
	Loss Function	MSE
SeNoCe [14]	Learning rate	0.1
	Epochs	120
	Batch size	32

	Dropout rate	0.9
	Activation Function	ReLU
	Optimizer	Adam
MATNN[17]	Learning rate	0.01
	Weight decay	0.03
	Epochs	100
	Batch size	64
	Optimizer	Adam
	Loss Function	Cross Entropy (CE)
FSRD[21]	Learning Rate	0.00001
	Batch Size	20
	Epoch	50
	Optimizer	Adam
DSMM [23]	Learning Rate	0.00001
	Epochs	100
	Activation Function	ReLU
	Dropout rate	0.9
Proposed BERT-ABSTRGCN model	Residual Branching Point	28
	Learning rate	0.001
	Weight decay	0.0002
	Epochs	150
	Batch size	24
	Momentum	0.9
	Dropout rate	0.5
	Activation Function	ReLU
	Optimizer	Stochastic Gradient Descent (SGD)
	Loss Operation	CE

- **Accuracy:** It defines the percentage of accurate predictions of rumors and non-rumors instances by classifier

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

Here, True Positives (TP) refer to tweets that are correctly identified as rumors, while True Negatives (TN) are tweets correctly identified as non-rumors. Tweets that are wrongly identified as rumors is False Positives (FP) and non-rumors are identified as rumors are False Negatives (FN).

- **Precision:** It defines the fraction of completely accurate positive predictions relative to the total number of positive predictions.

$$Precision = \frac{TP}{TP + FP} \quad (6)$$

- **Recall:** It assesses the model's effectiveness in accurately detecting all relevant positive instances.

$$Recall = \frac{TP}{TP + FN} \quad (7)$$

- **F-measure:** Precision and recall measures are simply represented as harmonic measures.

$$F - measure = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (8)$$

4.3 Performance Evaluation on PHEME Dataset

The proposed BERT-ABSTRGCN model is compared with DFFRD [12], ACSLF [13], SeNoCe [14] MATNN [17], FSRD [21] and DSMM [23] on PHEME dataset using different performance metrics like accuracy, precision, recall and f1-score which is illustrated in section 4.2. Figure (4) depicts the confusion matrix for the proposed work for test dataset instances 18734 numbers, which is described in section 4.1.

		Confusion Matrix	
		Non-Rumor (0)	Rumor (1)
Actual	Non-Rumor (1)	13958	619
	Rumor (0)	170	3987
		Non-Rumor (0)	Rumor (1)
		Predicted	

Figure 4. Confusion Matrix for the Proposed Model on PHEME Dataset

Performance Analysis on PHEME Dataset

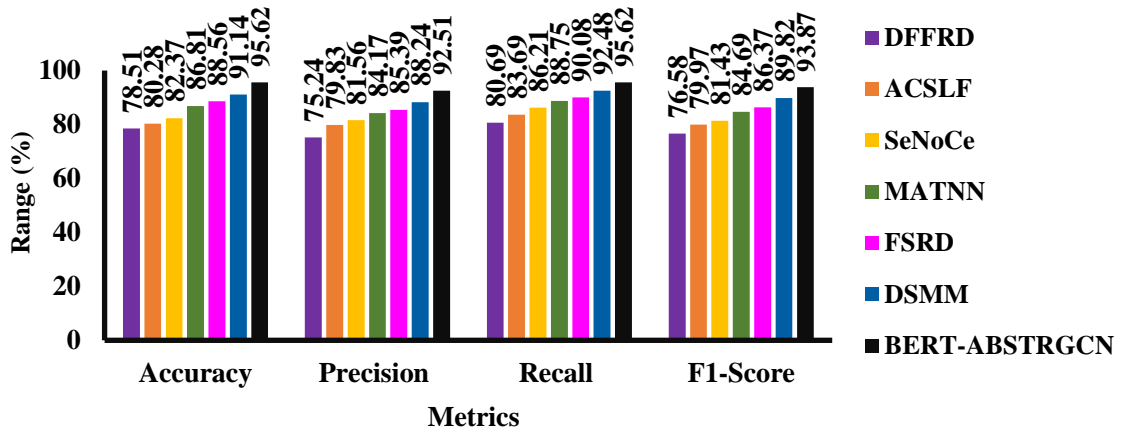


Figure 5. Performance Comparison on Rumor with Stance Detection on PHEME Dataset

Figure (5) illustrates the performance of different models on PHEME dataset for rumor stance prediction. It declares that the success rate of the BERT-ABSTRGCN model regarding precision, recall, f1-score and accuracy is greater than that of all other earlier models. It realizes that the accuracy of the BERT-ABSTRGCN is 21.79% superior to DFFRD, 19.11% superior to ACSLF, 16.09% superior to SeNoCe, 10.15% superior to MATNN, 7.97% superior to FSRD and 4.92% superior to DSMM. Accordingly, the precision of BERT-ABSTRGCN is 22.95%, 15.88%, 13.43%, 9.91%, 8.34% and 4.83% is higher than DFFRD, ACSLF, SeNoCe, MATNN, FSRD and DSMM models. The recall of BERT-ABSTRGCN is 18.5%, 14.25%, 10.92%, 7.74%, 6.15% and 3.39% is higher than DFFRD, ACSLF, SeNoCe, MATNN, FSRD and DSMM models, respectively. The F1-score of the BERT-ABSTRGCN is 22.58%, 17.38%, 15.28%, 10.84%, 8.68% and 4.51% is higher than DFFRD, ACSLF, SeNoCe, MATNN, FSRD and DSMM models, respectively. From this analysis, it is revealed that the proposed BERT-ABSTRGCN model surpasses all existing models, demonstrating the highest efficiency metrics across various evaluation scenarios on PHEME dataset.

4.4 Performance Evaluation on Mendeley’s COVID-19 Rumor Dataset

The proposed BERT-ABSTRGCN model is compared with DFFRD [12], ACSLF [13], SeNoCe [14] MATNN [17], FSRD [21] and DSMM [23] on Mendeley’s COVID-19 Rumor dataset using different performance metrics like accuracy, precision, recall and f1-score which is illustrated in section 4.2. Figure (6) depicts the confusion matrix for the proposed work for test dataset Mendeley’s COVID-19 Rumor Dataset.

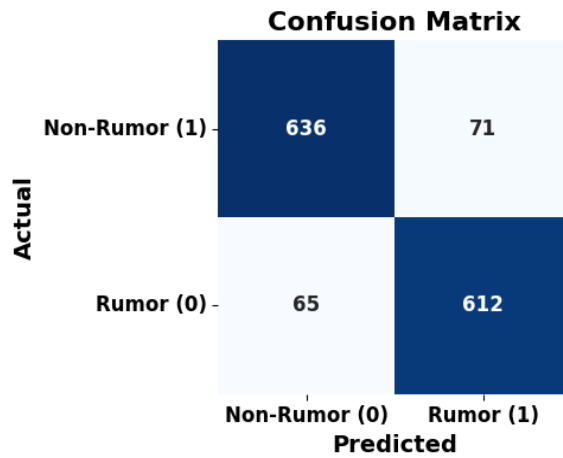


Figure 6. Confusion Matrix of Proposed Model on Mendeley’s COVID-19 Rumor Dataset

Figure (7) shows the performance of different models on Mendeley’s COVID-19 Rumor dataset for rumor stance prediction. The results indicate that the BERT-ABSTRGCN model consistently outperforms all other models in precision, recall, F1-score, and accuracy. Specifically, the accuracy of BERT-ABSTRGCN is 31.87% superior to DFFRD, 26.89% superior to ACSLF, 21.72% superior to SeNoCe, 12.68% superior to MATNN, 9.70% superior to FSRD, and 5.77% superior to DSMM. In terms of precision, the improvements are 34.11%, 21.38%, 17.51%, 12.32%, 10.19%, and 5.66%, respectively. For recall, the gains are 25.83%, 18.77%, 13.78%, 9.39%, 7.32%, and 3.91%, respectively. Finally, for the F1-score, BERT-ABSTRGCN achieves 33.43%, 23.88%, 20.41%, 13.67%, 10.65%, and 5.27% higher values compared to DFFRD, ACSLF, SeNoCe, MATNN, FSRD, and DSMM, respectively. This analysis clearly demonstrates that BERT-ABSTRGCN delivers the highest efficiency metrics across all evaluation criteria on Mendeley’s COVID-19 Rumor dataset.

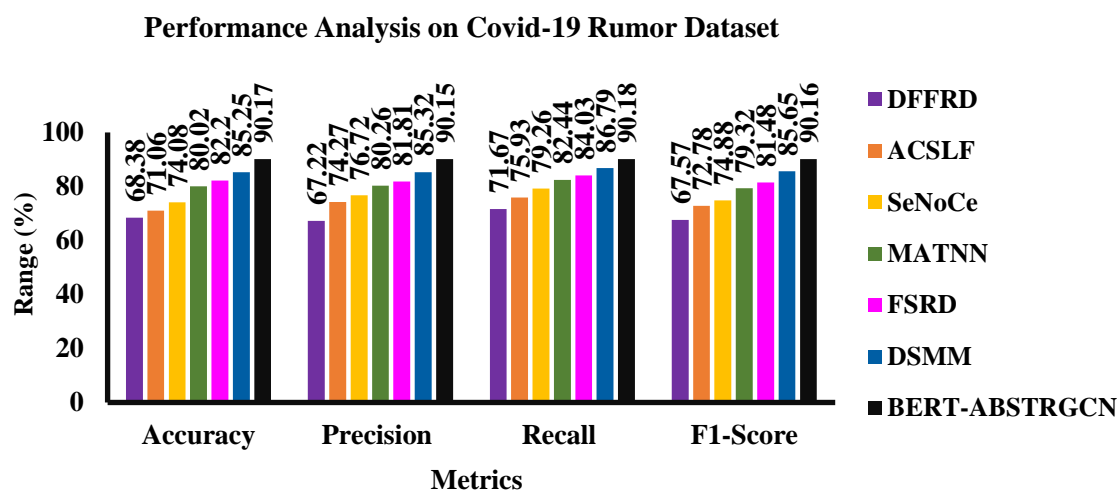


Figure 7. Performance Comparison on Mendeley’s COVID-19 Rumor Dataset

4.5 Performance Evaluation On Cross Residual Learning Models

The suggested BERT-ABSTRGCN model is compared with RL mechanism in BERT-ResNet50 on both PHEME and Mendeley’s COVID-19 Rumor dataset using the evaluation metrics.

In Figure (8), the performance of BERT-ResNet50 and BERT-ABSTRGCN is compared on the PHEME dataset using accuracy, precision, recall, and F1-score. The proposed BERT-ABSTRGCN achieves improvements of 4.45%, 5.58%, 18.89% and 4.64% over BERT-ResNet50 for these metrics, respectively. Similarly, Figure (9) presents the comparison on.

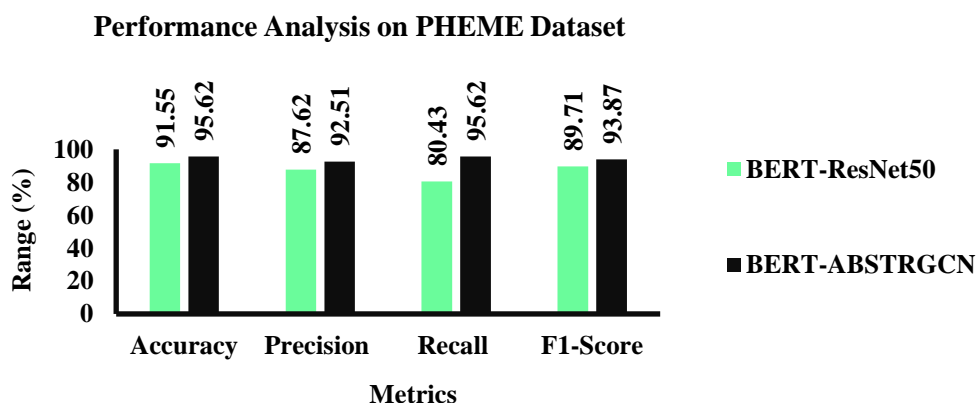


Figure 8. Analysis of CRL and existing RL on PHEME Rumor dataset

Performance Analysis on Covid-19 Rumor Dataset

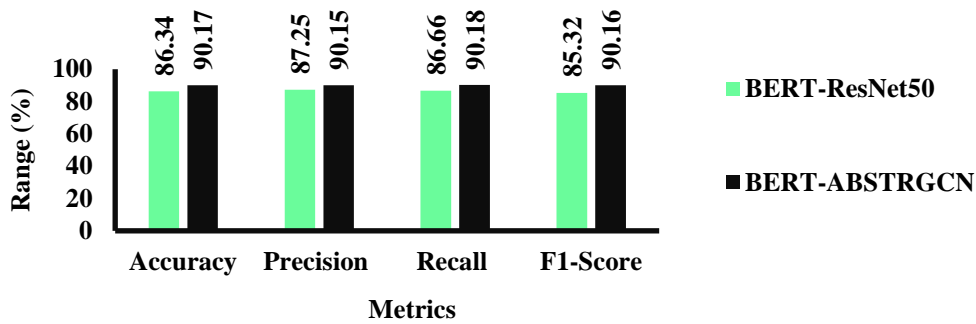


Figure 9. Analysis of proposed and existing Model on Mendeley’s COVID-19 Rumor dataset

Mendeley’s COVID-19 Rumor dataset, where BERT-ABSTRGCN records gains of 4.44% in accuracy, 3.32% in precision, 4.06% in recall and 5.67% in F1-score. These results demonstrate that the proposed model consistently outperforms its RL-based counterpart across all evaluation metrics. This is because the model uses identity mappings with short-cut connections to facilitate the multitask network instead of requiring one network per task to jointly perform rumor detection and stance classification, allowing for specialization per task and overall generalization.

4.5 Real Time IoT Deployment

The proposed BERT-ABSTRGCN model can be deployed in real-time IoT environments by running directly on edge devices such as IoT gateways, embedded AI processors or local monitoring servers connected to social media data streams via Application Programming Interfaces (APIs). Once interaction data are received, the BERT module tokenizes and encodes the text to produce context-aware embedding that capture nuanced linguistic meaning; ABSTRGCN captures most relevant user interactions. The CRL mechanism integrates outputs across tasks enabling the model to simultaneously predict rumour and stance categories with improved stability and reduced convergence issues. Running the full inference pipeline locally on the IoT device allows for sub-second predictions, minimal network bandwidth usage, and preservation of sensitive data. Detected rumours trigger automated alerts or updates on IoT dashboards, supporting continuous large-scale monitoring and rapid decision-making in applications such as disaster response, public safety, and misinformation control.

5. Conclusion

In this paper, BERT-ABSTRGCN is designed to overcome the performance degradation caused by convergence of DL models in rumor detection and stance categorization. This approach employs the CRL to enable intuitive learning across various tasks, including rumor detection and stance categorization. The CRL connects low-level and high-level features and addresses the vanishing gradient problem by incorporating an identity mapping function into the network. This identity map uses short-cut interactions to learn the underlying mapping and adjusts it through various layers to increase network depth. The fitted residual mappings in CRL accelerates the ABSTRGCN and lower the possibility of model’s degradation. This model effectively distinguishes various perspectives or attitudes towards particular social media posts and offers crucial measures to prevent rumor stance from spreading. On both datasets, BERT-ABSTRGCN achieved high accuracy, outperforming existing models. However, its reliance on BERT embedding and graph convolution increases computational demands, posing challenges for resource-constrained settings. Future work may explore lightweight encoders (e.g., DistilBERT, A Light BERT) and efficient graph models (e.g., LightGCN, GraphSAGE) to reduce cost while maintaining accuracy.

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References

- [1] Z. H. Ali, H. A. Ali, and M. M. Badawy, "Internet of Things (IoT): definitions, challenges and recent research directions," *Int. J. Comput. Appl.*, vol. 128, no. 1, pp. 37-47, 2015.
- [2] L. Atzori, A. Iera, G. Morabito, and M. Nitti, "The social internet of things (SIoT)—when social networks meet the internet of things: Concept, architecture and network characterization," *Comput. Netw.*, vol. 56, no. 16, pp. 3594-3608, 2012.
- [3] M. S. Roopa, S. Pattar, R. Buyya, K. R. Venugopal, S. S. Iyengar, and L. M. Patnaik, "Social Internet of Things (SIoT): Foundations, thrust areas, systematic review and future directions," *Comput. Commun.*, vol. 139, pp. 32-57, 2019.
- [4] Dang, M. Smit, A. Moh'd, R. Minghim, and E. Milios, "Toward understanding how users respond to rumours in social media," in *Proc. IEEE/ACM Int. Conf. Adv. Soc. Netw. Anal. Mining (ASONAM)*, 2016, pp. 777-784.
- [5] P. Zheng, Z. Huang, Y. Dou, and Y. Yan, "Rumor detection on social media through mining the social circles with high homogeneity," *Inf. Sci.*, vol. 642, p. 119083, 2023.
- [6] N. Alturayef, H. Luqman, and M. Ahmed, "A systematic review of machine learning techniques for stance detection and its applications," *Neural Comput. Appl.*, vol. 35, no. 7, pp. 5113-5144, 2023.
- [7] AlDayel and W. Magdy, "Stance detection on social media: State of the art and trends," *Inf. Process. Manag.*, vol. 58, no. 4, p. 102597, 2021.
- [8] H. F. Alsaif and H. D. Aldossari, "Review of stance detection for rumor verification in social media," *Eng. Appl. Artif. Intell.*, vol. 119, p. 105801, 2023.
- [9] Z. Mohammadhosseini and A. Jalaly Bidgoly, "Efficient Stance Ordering to Improve Rumor Veracity Detection," *J. AI Data Min.*, vol. 11, no. 1, pp. 69-76, 2023.
- [10] B. Pattanaik, S. Mandal, and R. M. Tripathy, "A survey on rumor detection and prevention in social media using deep learning," *Knowl. Inf. Syst.*, pp. 1-42, 2023.
- [11] Kumar, M. P. S. Bhatia, and S. R. Sangwan, "Rumour detection using deep learning and filter-wrapper feature selection in benchmark twitter dataset," *Multimedia Tools Appl.*, vol. 81, no. 24, pp. 34615-34632, 2022.
- [12] Z. Luo, Q. Li, and J. Zheng, "Deep feature fusion for rumor detection on twitter," *IEEE Access*, vol. 9, pp. 126065-126074, 2021.
- [13] Z. Zojaji and B. Tork Ladani, "Adaptive cost-sensitive stance classification model for rumor detection in social networks," *Soc. Netw. Anal. Min.*, vol. 12, no. 1, p. 134, 2022.
- [14] S. Roy, M. Bhanu, S. Dandapat, and J. Chandra, "Towards an orthogonality constraint-based feature partitioning approach to classify veracity and identify stance overlapping of rumors on twitter," *Expert Syst. Appl.*, vol. 208, p. 118175, 2022.
- [15] W. Cui and M. Shang, "KAGN: knowledge-powered attention and graph convolutional networks for social media rumor detection," *J. Big Data*, vol. 10, no. 1, p. 45, 2023.
- [16] Z. Chen, L. Wang, X. Zhu, and S. Dietze, "TSNN: A Topic and Structure Aware Neural Network for Rumor Detection," *Neurocomputing*, vol. 531, pp. 114-124, 2020.
- [17] N. Bai, F. Meng, X. Rui, and Z. Wang, "A multi-task attention tree neural net for stance classification and rumor veracity detection," *Appl. Intell.*, vol. 53, no. 9, pp. 10715-10725, 2023.
- [18] N. Alturayef, H. Luqman, and M. Ahmed, "Enhancing stance detection through sequential weighted multi-task learning," *Soc. Netw. Anal. Min.*, vol. 14, no. 1, p. 7, 2023.

- [19] W. Feng, Y. Li, B. Li, Z. Jia, and Z. Chu, "BiMGCL: rumor detection via bi-directional multi-level graph contrastive learning," *PeerJ Comput. Sci.*, p. e1659, 2023.
- [20] Y. Zhu, G. Wang, S. Li, and X. Huang, "A Novel Rumor Detection Method Based on Non-Consecutive Semantic Features and Comment Stance," *IEEE Access*, vol. 11, pp. 1-9, 2023.
- [21] H. Li, W. Yang, H. Wang, and W. Wang, "FSRD: few-shot fuzzy rumor detection system with stance-enhanced prompt learning," *Soft Comput.*, pp. 1-15, 2024.
- [22] N. Luo, D. Xie, Y. Mo, F. Li, C. Teng, and D. Ji, "Joint rumor and stance identification based on semantic and structural information in social networks," *Appl. Intell.*, vol. 54, no. 1, pp. 264-282, 2024.
- [23] G. Ma, C. Hu, L. Ge, and H. Zhang, "DSMM: A dual stance-aware multi-task model for rumour veracity on social networks," *Inf. Process. Manag.*, vol. 61, no. 1, p. 103528, 2024.
- [24] N. Michelle, "PHEME dataset for rumour detection," Kaggle, 2021. [Online]. Available: <https://www.kaggle.com/datasets/nicolemichelle/pHEME-dataset-for-rumour-detection>
- [25] B. Janssens, L. Schetgen, M. Bogaert, M. Meire, and D. Van den Poel, "COVID-19 rumor detection," Mendeley Data, V1, 2022. [Online]. Available: <https://data.mendeley.com/datasets/xcz8vb448y/1>