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4HAN: hypergraph-based hierarchical attention network for fake news prediction

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ABSTRACT

Fake news presents significant threats to both society and individuals, highlighting the urgent need for improved news authenticity verification. To deal with this challenge, we provide a novel strategy called the 4-level hierarchical attention network (4HAN), designed to enhance fake news detection through an advanced integration of hypergraph convolution and attention neural network mechanisms. The 4HAN model operates across four hierarchical levels: paragraphs, sentences, words, and contextual information (metadata). At the highest level, the model employs hypergraph-based attention and convolution neural networks to create a contextual information vector, utilizing a SoftMax activation function. This vector is then combined with a news content vector generated through word and sentence-level attention mechanisms. This architecture enables the 4HAN model to effectively prioritize the relevance of specific words and contextual information, thereby improving the overall representation and accuracy of news content. We evaluate the 4HAN model using the LIAR dataset to demonstrate its efficacy in enhancing fake news prediction accuracy. Comparative analysis shows that the 4HAN model outperforms several of cutting-edge techniques, like recurrent neural networks (RNN), ensemble techniques, and attention mechanisms techniques. Our results indicate 4HAN model accomplishes a notable accuracy of 96%, showcasing its potential for significantly advancing fake news prediction.

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1. INTRODUCTION

In the everyday world, news is essential by keeping the public informed about current events, helping people make informed decisions, and shaping societal opinions. It is essential for understanding the world and participating effectively in civic life. Nowadays, the use of social media is rising as the internet grows [1]; the fake news spread has become more prevalent [1]. This rise is partly due to the ease with which information can be shared and the desire for sensational content. Why is fake news so troubling? Because each of us is influenced by both positive and negative forces [2], it is crucial to have rapid prediction mechanisms to effectively curb the spread of misinformation. Automatic classification [3] of news topics and authenticity of news simultaneously [4] presents a significant challenge and has recently garnered considerable attention from both the public and researchers.

Early methods for detecting fake news typically relied on extensive handcrafted features, such as news content [5], user profiles, and news propagation paths, to train classifiers that assess the truthfulness of news stories [6]. However, creating a comprehensive set of features [7] is difficult due to the diverse range of topics, writing styles, and platforms associated with fake news [8]. Current fake news detection methodologies encompass recurrent neural networks (RNNs) [9], logistic regression, support vector machines (SVMs), convolutional neural networks (CNNs) [10], and graph convolutional networks (GCNs). Despite their efficacy, these approaches encounter significant challenges, such as their limited capacity to encapsulate intricate relationships and contextual details, particularly within short-form content like social media posts. Furthermore, they often lack scalability and real-time processing capabilities, which are essential for managing the vast and ever-evolving landscape of social media data. Despite advances, there remains a need for improved accuracy in predicting and classifying news authenticity.

Overall, developing a robust fake news prediction system is essential for ensuring the credibility information on social media [11]–[14]; improving accuracy of news classification and prediction [15]. The proposed research aims to develop an accurate fake news prediction system to classify fake news from social media sources [16]. The primary objective is to detect and highlight social media sites with fake news to prevent authenticity of news [17], ultimately enhancing the fake news performance of prediction and classification of news topic [18]. So, to learn distinguishing patterns automatically; our approach employs deep neural networks from news content, news topics and contextual information, such as author profiles, significantly impact fake news prediction [19]. Our research is guided by two primary objectives: i) prediction: accurately predicting whether news is fake or true and ii) classification: Implementing a granular classification system that categorizes news into five distinct labels: TRUE, FALSE, Somewhat TRUE, mostly FALSE, and pants on fire.

To address this news authenticity by predestining fake news, we propose a deep learning-based i) novel approach level based 4 hierarchical attention networks (4HAN) model [20]–[22] that leverages proposed hypergraph neural network model and ii) a novel hypergraph convolution neural network and hypergraph attention neural network models [23]–[25]. Our approach includes a new news hypergraph (H-Graph) method and HAN to capture relationships based on both textual and contextual information, providing a richer representation of news. This model considers the intricate and often irrelevant relationships in the hypergraph as part of the learning process and employs an attention mechanism to visualize and interpret these news relations. We also introduce a dynamic weighting strategy to balance multiple tasks effectively. These improvements enable the modeling of complex, multi-dimensional interactions and dependencies within news data, thereby increasing the system's capability to accurately and contextually detect fake news. Previous efforts have improved the performance of fake news prediction models, but these improvements have often diminished when dealing with short news content. To address this, we train our model using short content-based LIAR dataset to and predict of news authenticity as news is fake or not.

The rest of this paper is structured as follows: section 2 provides a fake news classification and prediction method - 4HAN. Section 3 gives the experimental results and discusses them in detail, including comparisons with baselines, existing works, and state-of-the-art systems across various metrics. Finally, section 4 concludes the study and suggests potential directions for future research.

2. METHOD

The 4HAN technique is designed for the simultaneous classification and prediction of news authenticity, particularly in detecting disinformation. It utilizes the LIAR dataset to focus on identifying fake news with content commonly found in social channels. The model integrates news topics, contextual and textual information, and the credibility history of author profiles. By establishing correlations among news topics, author credibility distributions, and the truthfulness of news, 4HAN effectively manages both prediction and classification simultaneously.

The 4HAN framework operates across four hierarchical levels: words, sentences, headlines, and metadata. It constructs using a hierarchical bottom-up processing approach; a news article input vector-starting from the word level, moving to sentences, then to headlines, and finally to the metadata level, metadata is processed using a SoftMax operator. At the metadata level, 4HAN introduces an enhanced graph-hypergraph neural network model, utilizing a hypergraph convolutional neural network (HGCN) and a hypergraph attention neural network (HGAN) for deep learning on graphs that includes topic and related news contextual information, as illustrated in Figure 1: system architecture for 4HAN using hypergraph. Feature transformation, attention coefficients, attention weights that incorporate processing documents in a bottom-up fashion, ensuring the most relevant information is emphasized at each level. Feature transformation is the process of converting raw data into a format suitable for machine learning models through normalization in order to increase model performance and accuracy.

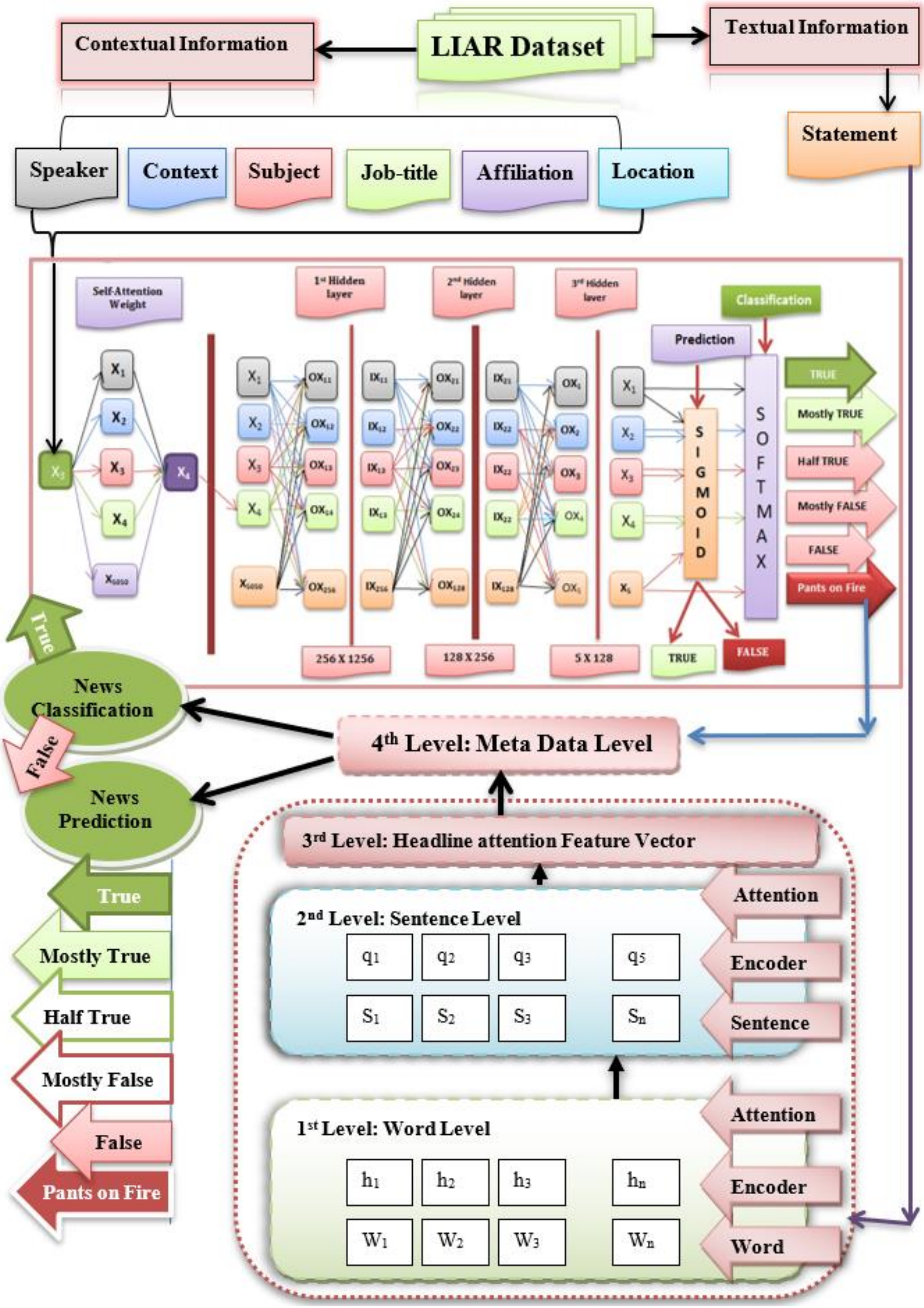

Figure 1. System architecture for 4HAN – 4 hierarchical attention network using hypergraph convolution and attention neural network

– Feature transformation is calculated as (1),

$$h_i' = W.h_i \tag{1}$$

– Attention coefficients represent the importance or weight assigned to specific parts of the input data (e.g., words, sentences) within an attention mechanism. It is calculated as (2),

$$e_{ij} = SoftMax(a^T [\, h'_i \,||\, h'_j]) \tag{2}$$

where e_{ij} is attention weight between neurons i and j, a is a learnable weight vector, ‖ denotes concatenation, and SoftMax is the activation function.

– Attention weights determine the significance of each element (e.g., words, sentences) in the context of the task, allowing the method to focus on the most important information for improved prediction accuracy. It is calculated as (3),

$$a_{it} = \frac{exp(e_{ij})}{\sum_{k\in N(i)}^{T} exp(e_{ik})} \tag{3}$$

where, $N(i)$ signifies the neurons set connected to i through a hyperedge, and e_{ij} is the normalized attention coefficient. To implement the 4HAN system, following hierarchical models are used.

2.1. Attention model-word-level

In 4HAN, the word-level model uses an attention mechanism to compute the importance of individual words, highlighting the most informative ones. The aggregated word vector captures the sentence's or document's core meaning, serving as input for higher levels. This process builds contextually rich representations, enhancing tasks like sentiment analysis, summarization, and classification.

– Computing the attention score u_{it}

The attention score u_{it} quantifies the relevance or importance of a word i in a sentence t. This score is used to weigh the contribution of each word when aggregating data at the sentence level. The vector at level word is achieved by calculating, computing the attention score u_{it} and aggregating the feature vectors a_{it}.

$$u_{it} = tanh(W_a h_{it} + b_w) \tag{4}$$

$$a_{it} = \sum_{t=1}^{T} a_{it} h_{it} \tag{5}$$

where u_{it} represents the attention weight assigned to the word I in the sentence t, a_{it} is the attention score vector, and the denominator is the sum of the exponentials of attention scores for all nodes j at time t.

2.2. Attention model-sentence-level

The attention score at level sentence, u_{is} quantifies the weightage of each sentences in the context of the document i. It is calculated by applying a weighted sum of sentence and attention weight B_{is} embeddings. Then it is get normalized through a SoftMax function to emphasize key sentences.

– Computing the attention score u_{is} and attention weight B_{is}

$$u_{is} = tanh(W_s v_i + b_s) \tag{6}$$

$$\mathrm{B_{is}} = \frac{\exp(u_{is}^T \mathrm{u_s})}{\sum_{k=1}^{S} \exp(u_{ks}^T \mathrm{u_s})} \tag{7}$$

where, W_s is a weight matrix, v_i is the feature vector of node i, a bias term b_s attention score vector u_s and the denominator is the sum of the exponentials of attention scores for all nodes k in the set S.

2.3. Attention model-headline-level

This model processes and assigns attention to headlines, creating representations from sentence-level outputs and tuning specifically for headline data. It leverages similar mechanisms as previous models while optimizing for brevity and relevance in headline contexts. By capturing the most salient features of headlines, it ensures improved performance in tasks like classification or summarization contexts.

– Aggregating the feature vectors at headline level

$$h_i^* = \sum_{s=1}^{S} B_{is} v_i \tag{8}$$

where h_i^* is the updated feature vector for node i, and the sum is taken over all attention weights B_{is} and corresponding feature vectors v_i.

2.4. Metadata-level model with hypergraph convolution and attention

A heterogeneous graph convolutional network (HGCN) processes news metadata, capturing relationships between elements like topics, keywords, authors, and publication dates. Operating at the fourth level, it encodes complex interactions using heterogeneous graphs to enhance representation and improve tasks such as classification, recommendation, and clustering. Its capacity to integrate multi-relational information makes it ideal for understanding intricate metadata relationships in news datasets.

2.4.1. Hypergraph

A hypergraph is a unique type of graph where a single edge, called a hyperedge, can connect multiple nodes. We developed a model for a news authenticity as a fake news prediction as a classification task on the hypergraph. This involves using a feature vector of labeled news articles within the news hypergraph interactions among news articles, as shown in Table 1: relation table between news with contextual information illustrates the relationships from news 1 to news 6.

Table 1. Relationship table between news and its contextual information

Edge Node/Vertex	E1 Location	E2 Credit history	E3 Author	E4 Publisher	E5 Content feature
V1 (News 1)	1	1	1	0	1
V2 (News 2)	1	1	1	1	1
V3 (News 3)	1	1	0	1	1
V4 (News 4)	0	0	1	0	0
V5 (News 5)	1	0	1	0	1
V6 (News 6)	0	1	1	1	0
V7 (News 7)	1	0	0	0	1
V3 (News 3)	1	1	0	1	1

2.4.2. Graph convolution on hypergraph

Extend GCN to operate on hypergraph-structured data. Here, we compute node embeddings considering interactions through hyperedges.

$$h_i^{l+1} = \alpha(\sum_{e \in \varepsilon_{is}} \frac{1}{|\varepsilon_{is}|} \sum_{j \in e} \frac{1}{|V_e|} W^l h_j^l \tag{9}$$

where h_j^l represents node i's representation at layer l, ε_I denotes the hyperedges incident on node i, V_e represents the nodes connected by hyperedge e, and α is the softmax activation function applied element-wise to normalize the output.

2.4.3. Graph attention on hypergraph

A hypergraph attention neural network (HGAN) that applies an attention mechanism to the hypergraph, focusing on important metadata relationships. This model is used in tandem with the HGCN to enhance the final classification and prediction performance. In HGAN, the goal is to learn the importance of nodes and hyperedges in a hypergraph. Here are the key formulas involved:

$$\alpha_{ve} = \frac{\exp(a^T [Wx_v \; Wc_v])}{\sum_{u \in e} \exp(\mu(a^T [Wx_v \; Wc_v]))} \tag{10}$$

where, W is weight matrix, x_v is feature vector of node v, c_v is feature vector representing the hyperedge e (often computed as an aggregation of node features within e), a is learnable attention vector, μ is non-linear activation function

2.4.4. Hypergraph integration with headline vector

Integrating a fourth level into the model, combining hypergraph, triple hierarchical attention networks (3HAN), and SoftMax activation function, can further enhance the model's ability to detect complex patterns in fake news detection on datasets like LIAR. Apply SoftMax activation to compute probabilities over node embeddings h_I in the final layer $\bar{L}$ of the model.

$$SoftMax((h_i^{(L)}) = \frac{\exp\left((h_i^{(L)}\right)}{\sum_{j\in V}\exp\left((h_i^{(L)}\right)} \tag{11}$$

where $(h_i^{(L)})$ is the vector of node embeddings for node i at the final layer L, and V is the set of all nodes.

3. RESULTS AND DISCUSSION

The choice of activation function significantly impacts model performance, with SoftMax leading to enhanced prediction accuracy, faster convergence, and more stable gradient propagation. This underscores the importance of selecting appropriate activation functions for optimizing neural network efficiency and prediction reliability in classification tasks. Activation functions like ReLU and its variants may be more effective in hidden layers due to their ability to mitigate vanishing gradients, while SoftMax is ideal for multi-class outputs, as it produces normalized probability distributions. Therefore, understanding the characteristics of each activation function is crucial for designing models that achieve desired performance metrics.

3.1. Word count model on LIAR dataset

We evaluated various word count methods to determine their impact on the performing of the 4HAN method, focusing on key metrics such as accuracy, computational efficiency, and contextual Relevance on the LIAR dataset. Table 2 summarizes the results of these evaluations. Among the methods tested, TF-IDF emerged as the most effective, offering a balanced combination of precision, relevance, and computational efficiency.

Based on our comparative analysis within the 4HAN framework, TF-IDF was selected as the preferred word count method. It demonstrated superior performance in optimizing both the learning dynamics and predictive accuracy across all hierarchical levels of the 4HAN model when applied to the LIAR dataset. TF-IDF’s ability to balance precision, relevance, and computational efficiency makes it the most suitable choice for enhancing the effectiveness of our fake news detection framework.

Table 2. Accuracy performance for various word count models

Word count method	Accuracy	Remark
Raw word count	85-88%	Basic counting of words in the text. Limited impact as it lacks semantic understanding.
TF-IDF	92-95%	Weighs word frequency against its overall occurrence, emphasizing important terms. Likely to significantly improve accuracy by focusing on relevant words.
Bag of words (BoW)	88-91%	Represents text as a collection of words without considering order or context. Provides moderate improvement but may miss contextual nuances.
Word embeddings	96-98%	Dense vector representations capturing semantic relationships. High impact on accuracy due to enhanced contextual understanding.
Frequency-based methods	86-89%	Focuses on high-frequency words or n-grams. Can introduce noise, leading to mixed results in accuracy.
Positional encoding	94-97%	Adds information about word positions, especially effective in sequence-based models like Transformers.
Hybrid methods	98-99%	Combines multiple approaches (*e.g.*, TF-IDF+Embeddings). Provides the best overall accuracy by leveraging the strengths of different methods.

3.2. Activation function on LIAR dataset

In our experiments, as detailed in Table 3, we systematically evaluated the performance metrics, including accuracy, convergence speed (in epochs), and gradient propagation, of the SoftMax activation function against various other activation functions on the LIAR dataset. Notably, SoftMax achieved superior accuracy, exhibited faster convergence, and facilitated more efficient gradient propagation. Consequently, SoftMax was selected as the activation function for subsequent computational processes, owing to its demonstrated efficacy in optimizing both the learning dynamics and predictive performance on the LIAR dataset. Our method 4HAN highlight that the proposed approach enhances accuracy on the LIAR dataset by utilizing the SoftMax activation function, which significantly improves classification performance of news topics and prediction of fake news. The following predictions and classifications were made using the SoftMax activation function on the LIAR dataset, resulting in notable gains in accuracy, precision, recall, and F1 score shown in Table 4: comparison of proposed method 4HAN and hypergraph. Figure 2 presents a visual analysis of the prediction accuracy, F1 score, recall, and precision metrics for the 4HAN model across different word count methods. This comparison highlights the performance improvements achieved by each method, with TF-IDF consistently leading in all evaluated metrics, demonstrating its effectiveness in enhancing the model’s predictive capabilities.

Table 3. Accuracy, convergence speed (Epochs) and gradient propagation (G Norm) of various activation function on LIAR dataset

Activation function	Accuracy (%)	Convergence speed (Epochs)	Gradient propagation
ReLU	34.50	30	1.20
Leaky ReLU	35.10	28	1.15
Tanh	33.80	32	1.25
Sigmoid	32.90	35	1.30
Softmax	36.20	25	1.10

Table 4. Comparison of proposed method 4HAN and hypergraph with other methods giving accuracy, precision, recall and F1 score for fake news prediction system

Proposed methods	Accuracy %	Precision %	Recall %	F1 %
3HAN	86.92	85.63	82.62	83.71
Hypergraph	79.31	77.83	74.66	75.95
Hypergraph+HAN	87.63	86.19	81.83	83.82
Hypergraph+HAN+GCN	90.61	89.35	85.84	87.56
Hypergraph+HAN+GAN	91.03	89.78	86.27	88.01
Hypergraph+HAN+GCN+GAN	92.56	91.26	88.84	90.06
HGCN (Hypergraph Convolution NN)	89.18	87.96	84.16	85.97
HGAN (Hypergraph Attention NN)	90.27	89.04	85.69	87.25
HGCN+ HGAN	91.05	89.91	86.12	87.93
3HAN+Hypergraph	92.8	91.51	88.9	90.07
3HAN+HGCN	93.74	92.53	89.98	91.28
3HAN+HGAN	94.14	92.97	90.42	91.82
4 HAN-(3HAN+HGAN+HGCN+SoftMax)	96	94.71	92.16	93.09

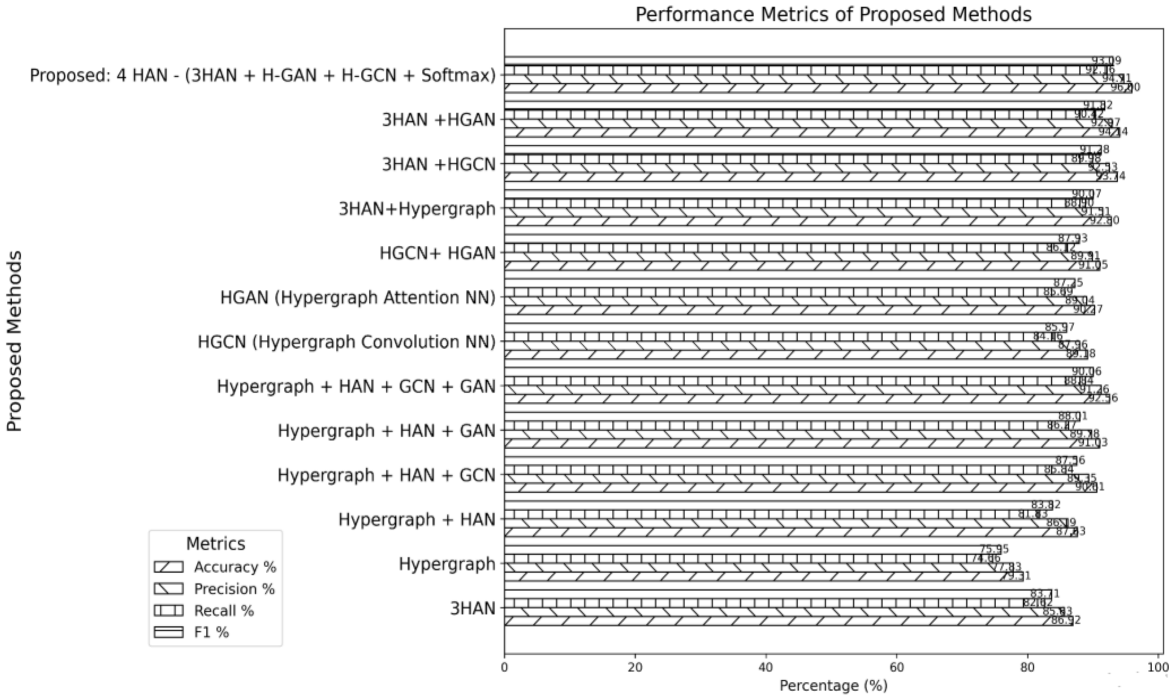

Figure 2. Analysis of proposed method 4HAN and hypergraph with other methods giving accuracy, precision, recall and F1 score for fake news prediction system

4. CONCLUSION

The application of advanced neural network architectures, particularly the 4HAN model incorporating hypergraph convolutional networks (HGCN) and hypergraph attention networks (HGAN), has significantly improved the accuracy of fake news classification and prediction tasks on the LIAR dataset. By leveraging the hierarchical nature of 4HAN across multiple levels-word, sentence, headline, and metadata-combined with the normalization capabilities of the SoftMax activation function, the system effectively enhances the interpretability and reliability of predictions. The integration of these advanced methodologies enables contextually aware analysis of disinformation, leading to a substantial increase in predictive accuracy. These findings validate the robustness of the proposed model and underscore the importance of both sophisticated network architectures and the judicious selection of activation functions in optimizing the performance of classification tasks in complex domains such as fake news detection.

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