Performance Analysis of GCN, GNN, and GAT Models with Differentiable Pooling for Detection of Fake News

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***Abstract*—In the era of social networks, the spread of fake news has become a critical issue that poses significant challenges to society. It is often difficult to distinguish between real news and fake news due to the sophisticated methods used to create misleading information. This paper presents a comprehensive approach to detecting fake news. The study conducts a systematic review of the performance of the Graph Convolutional Networks (GCN), Graph Attention Networks (GAT), and Graph Neural Networks using DiffPool (GNN-DP) in Twitter data. It takes into account the limitations identified in the previous studies and fine-tunes the parameters to obtain better results. Performance evaluation of the proposed model was done using metrics such as accuracy, F1 score, and area under the curve (AUC). In the results obtained, it is found that GCN, with its dynamic attention mechanism, outperforms GAT and GNN-DP by effectively highlighting the most relevant information within the graph. Next, we discuss the practical implications of fake news detection and the GCN model. Finally, we present the future scope in this area for further research.**

Keywords—Fake News Detection, Graph Neural Networks, Graph Convolutional Network, Graph Attention Network, Differentiable Pooling, Performance Analysis

I. Introduction

As defined in [1], Aimeur et al. have stated "Fake news is a news article that is intentionally and verifiably false and could mislead readers" [1]. This proliferated fake news consists of all sorts of information that can mislead the general public, who has limited exposure to social networks. With the everincreasing advancement in artificial intelligence (AI), social media, and networking, fake news is now easily generated and circulated, sometimes even going viral. Sometimes, this news can lead to a change in the belief of the masses, which is damaging, malicious, and even dangerous to society. As in [2], Touahri, I., Mazroui, A. in their survey, have stated that often the fraudulent actors take into account several other languages [3] to create the fake news in order to reduce the chances of being caught. And due to the lack of contextualizing the current state of research in this domain, the difficulty of the language and the lack of dataset for different languages, detecting the fake news poses a challenge. On 24 February 2017, a story shared by Marion Marechal-Le Pen, niece of National Front presidential candidate Marine Le Pen, claimed that the campaign of Emmanuel Macron, a centrist candidate, was financially supported by Saudi Arabia (Fig. 1).

Many fake news articles originate from the sarcasm and satire in the articles. Often the satirical content is misprinted to garner the attention of audience. Sarcasm recognition, even for humans, can be difficult to recognize. So doing a sentiment analysis and text featue extraction is a difficult task [4] [5]. Fkih, F., Rhouma, D., & Alghofaily, H. in their research takes into account Support Vector Machine (SVM) to recognize satire. Unlike traditional solutions, such as the human factcheckers used earlier, modern problems need modern solutions. Automatic Fact-Checkers' Consensus and Credibility Assessment (AFCC) system introduces a groundbreaking solution [6]. Various Deep Learning models such as Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), Convolutional Neural Network-LSTM (CNN-LSTM), CNN-BiLSTM [7] and, generative round network (GRN) [8]. This paper focuses on the comparisons of the results of three Machine Learning models such as GNN, GCN, and GAT, and analyzes which model provides a much better result. In this study, we have considered the Twitter social network graph, in which the (re)tweeting behavior is classified under edges, and Twitter users and news articles are nodes. The GCN approach used in the paper straddles the boundary between Graph ML and NLP. It spreads the text embedding of the nodes and pools them to produce a classification. As an alternative, our GNN-DP approach uses concepts from Convolutional Neural Networks (CNN) to generate the fine label by repeatedly combining predictions from different sub-graphs.

Fig. 1. A fake news site registered in the US cloned the website of reputable Belgian newspaper Le Soir to make the false allegations.

II. Literature Survey

The use of AI and other advanced technologies has made it possible to detect fake news, flaming, and other content on various social media platforms. However, the accuracy and efficiency of these technologies is a matter of concern. In this section, we summarize the work carried out in this domain.

In [9], Chandra et al. have proposed a fake news detection framework based on GNN. The proposed framework analyzes the content distributed on social networks, the behavior of users, and their peers. The proposed framework uses a graph-based approach for the detection of fake news. The results obtained with the proposed framework outperform the text-based models. In [10], Mahmud et al. have presented a detailed comparative analysis of machine learning approaches such as SVM, logistic regression, decision tree and random forest, and GNN-based techniques such as GAT, GCN, etc. The main objective of the authors was to minimize the content of fake news on social media. In [11], Phan et al. have discussed the various challenges that exist in the detection of fake news using GNN. They have also provided the GNN taxonomy for the detection of fake news. They also listed the various types of data sets for experimentation purposes and compared them. They have also categorized the features of fake news detection methods. Further, in their subsequent sections, they presented detection approaches based on GCN, GNN, graph autoencoders, and attention-based GNN. In [12], Guo et al. have presented a mixed GNN model for the detection of fake content in vehicular social networks. The proposed model considers CNN and the recurrent neural network (RNN). They have used existing social network data sets for experimentation purposes and improved the results by 5% to 15%.

In [13], Lu and Li have presented a realistic scenario for the detection of fake news considering the original tweet and the retweets of the other users with their profiles. They have proposed graph-aware co-attention networks (GCANs) to perform their experiments. The proposed model finds the susceptible retweet and the fake user profile. The results obtained represent an improvement of 16% from other methods. In [14] Meel and Vishwakarma have implemented a semi-supervised learning methodology for the text-based detection of fake news. They utilized a GCN-based architecture to gather words, construct similarity graphs, and perform binary classification of the news in the social network. Their experiments yielded an accuracy of more than 95%.

In [15], Ren and Zhang have proposed a Hierarchical Graph Attention Network(HGAT) for the detection of fake news. The proposed model uses the hierarchical information network for the representation of nodes. The authors have addressed major challenges such as heterogeneity, hierarchy, and generalizability with the proposed framework. In addition, they used the PolitiFact data set. In [16], Karnyoto et al. have proposed a fake news detection model related to COVID-19 news. The proposed model uses the augmentation and GNN-based approaches and considers the various types of nodes, such as word-word nodes and word-document nodes. They have used the data set that includes 10, 700 posts from various social media networks. During experimentations, they considered the various samples of the data set to perform the augmentation task and in their analysis. They have achieved the outperforming results. In [17], Dhawan et al. have proposed a GAME-ON a GNN-based end-to-end framework for the detection of fake news. For experiments that have used the Twitter and Weibo data sets. The proposed model outperforms the existing model in the Twitter dataset by 11%.

III. Methodology

This section details the methodology of the proposed technique across various subsections, including dataset description, preprocessing, and model initialization. These are discussed as follows:

A. Dataset

In this paper, we have used the existing data sets, i.e. Politifact and Gossipcop (statistics shown in Figure 2), that provide the various instances of Twitter communication. This data set consists of various tweets and retweets from the users. The news retweet graphs were originally extracted by FakeNewsNet. Here, Gossipcop deals mainly with various types of circulated news stories about movie stars related to their private or social life. This data set includes almost 20 million historical tweets from users on FakeNewsNet.

TABLE I. Statistics of the UPFD Dataset

Data	Number of Graphs	Number of Fake News Instances	Total Nodes	Total Edges	Average Nodes per Graph
PolitiFact	314	157	41,054	40,740	131
GossipCop	5464	2732	314,262	308,798	58

The GossipCop dataset is significantly larger, dense, and more complex than the Politifact dataset in terms of the number of graphs (5464), nodes (314, 262), and edges(308,798). The high number of graphs in Gossipcop provides more data for training and testing models. Though it might lead to generalization, we require high computer efficiency for it. The balanced ratio of fake to real news instances (50%) in both data sets makes them valuable for training and evaluating fake news detection models. However, if we carefully analyze the Politifact dataset, the average number of nodes per graph is higher in Politifact (131) than in Gossipcop (58). This could suggest that PolitiFact graphs are more complex on average.

This data set is included in the PyG package under the name UPFD, which stands for User Preference-aware Fake News Detection Dataset. It comprises 314 graphs, 157 of which are related to fake news. Each graph in this data set follows a hierarchical tree structure. Here, the root nodes represent the news article and the leaf nodes represent the retweeted users on Twitter. An edge between a user node and the news node signifies that the user has retweeted the news tweet. Additionally, an edge between two user nodes indicates that one user has retweeted the news tweet from the other user.

B. Preprocessing of Dataset

Data preprocessing is the most crucial step before we proceed with the training of our model. The preprocessing mainly revolves around preparing the UPFD (User Preference-aware Fake News Detection), Tweets encoded through the BERT (768-dimensional), and dataset for training, validation, and testing with a Graph Convolutional Network (GCN). We focus on two aspects: Cast the directed social media graph into undirected and loading node features, i.e., we will concatenate each user's profile attribute (10 dimensional) and encrypt their previous tweets using BERT (768 dimensional) for each news node and user.

C. Model Initialization

We have trained two models, GCN and GNN-DP, in this research. Each model offers benefits and drawbacks of its own.

1) Graph Convolution Network (GCN)

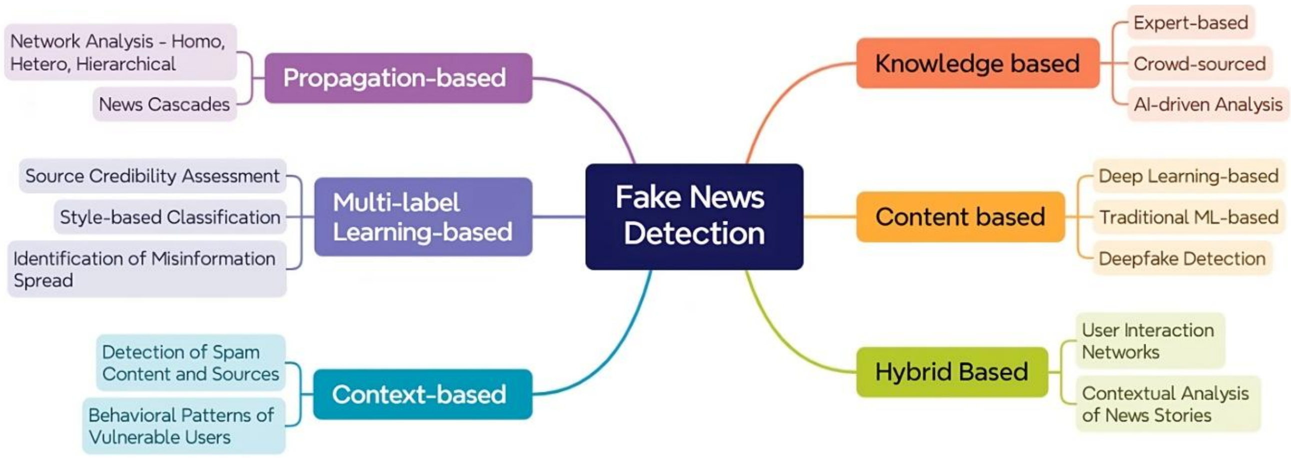

Fig. 2. Fake News Detection

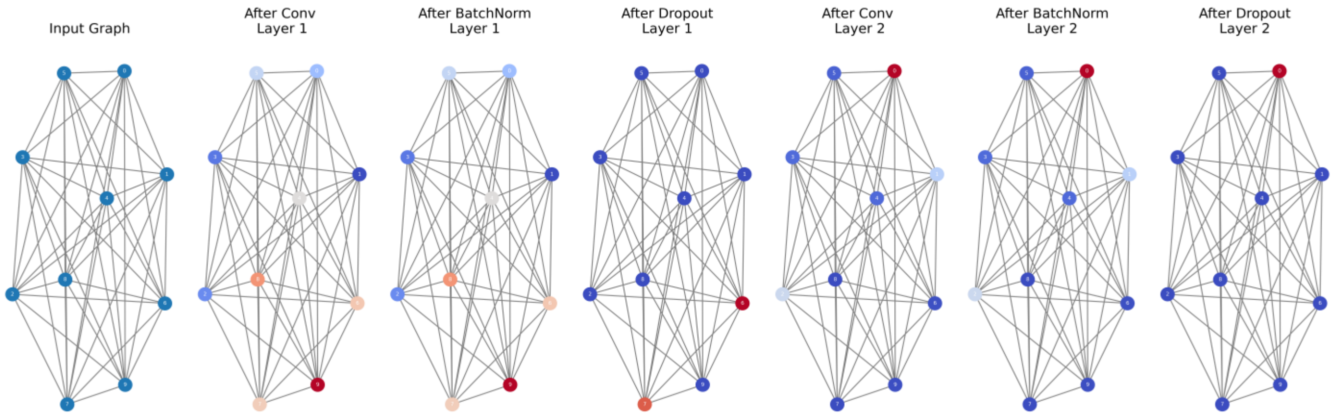

Fig. 3. Visualization of GCN Layers

a) The GCN model processes Twitter data by transforming it into a graph format, where the users and tweets are nodes, and interactions are edges. The model consists of multiple graph convolutional layers, batch normalization layers, and a final linear layer as shown in Fig. 2.

b) Each convolutional layer as shown in Fig. 3., applies graph convolutions to the input data, transforming node features by considering their neighbors' features.

c) Batch normalization layers are used between convolutional layers to stabilize and accelerate training.

d) The final linear layer maps the output of the convolutional layers to the desired number of output classes (e.g., fake or real news).

e) The model is trained by minimizing the negative log-likelihood loss between the predicted and true labels. The model is validated and tested to ensure it performs well on new, unseen data, with performance measured using various metrics like accuracy, F1 score, and AUC.

f) This approach enables the detection of fake news by capturing complex relationships and patterns in the data.

2) Graph Neural Network (GNN) with DiffPool Implementation

a) *Hierarchical Graph Representation Learning with Differentiable Pooling (DP)*: This model is highly effective for graph-level class predictions. Unlike the flat structure of the GCN, the GNNDP structure hierarchically generates predictions, as illustrated in Fig. 4.

b) *Parallel GNNs in GNN-DP*: The GNN-DP model includes 2 GNNs that operate simultaneously: (i) GNN A processes node embeddings, and (ii) GNN B maps nodes to a set of clusters.

c) *A differential pooling layer*: Is is used to update the embedding of the node in an adjacency matrix. This layer processes nodes from GNN A based on the cluster assignment from B.

d) *Custom GNN Module Constructions*: For parallel GNNs, the GNN-DP mode first builds a custom GNN module.

e) *Differential Pooling Modules*: These modules, utilizing pre-built GNNs, are responsible for cluster assignments and node embedding.

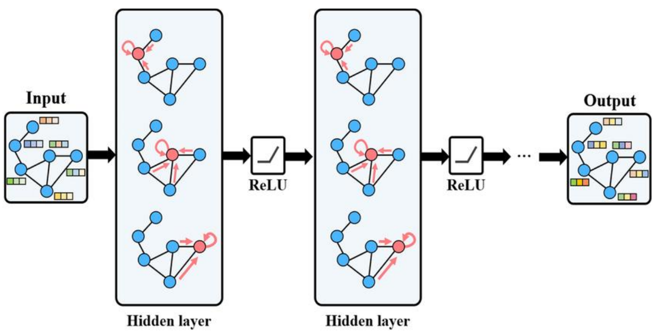

Fig. 4. GCN Model Architecture

f) *Cluster size Reduction*: The cluster size is sequentially reduced from 500 to 100, and then to 20 (a reduction of 20% each time). Differential pooling is applied twice before performing mean pooling and a linear transformation to produce the final softmax prediction.

g) *Design decisions*: A decision is made regarding the cluster reduction rate and the number of diffpool layers to use based on the characteristics of the data set, selecting the most suitable combination.

3) *Graph Attention Network (GAT)*

a) Graph Attention Networks (GAT) introduce the attention mechanism to graph-based neural networks, which allows the model to focus on the most relevant parts of the graph. This allows the model to weigh the importance of each neighboring node differently.

b) Attention scores are computed using learnable weight matrices, which are trained during the model training process. This makes the aggregation process dynamic and adaptive to different graph structures as shown in Fig. 5.

c) Unlike GCN, which uses a fixed weight for each neighbor, GAT uses attention scores that are dynamically computed based on the features of the nodes and their neighbors. This allows the model to learn more complex relationships.

d) GAT can potentially model more complex patterns in the data because it does not treat all neighbors equally. This makes it more expressive compared to GCN, which might fail to capture some nuanced relationships in the graph.

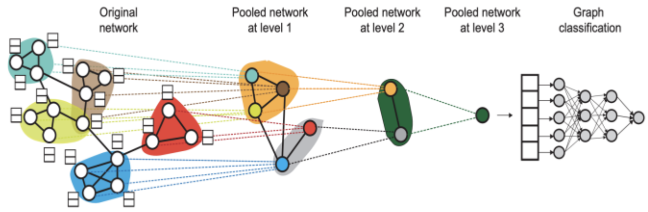

Fig. 5. GNN with DiffPool (for every hierarchical layer, we run the GNN model)

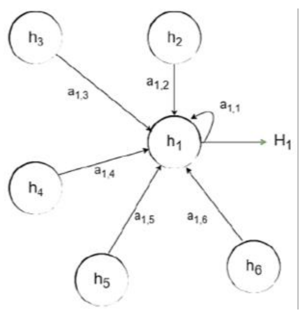

Fig. 6. Graph Attention Network

IV. Performance Analysis

For performance analysis, we have computed the different measures like F1-Score, Precision, Recall, Accuracy, and Area under Curve (AUC) by using the standard equations, respectively. Further, the plots obtained for the various measures are represented in Fig. 7(a), Fig. 7(b), Fig. 7(c), and Fig. 7(d) that visualize the performance of an ML model over multiple training epochs. In Fig. 7(a), the Training and Validation Accuracy curves show how the model's accuracy improves over time. As both curves are increasing, this demonstrates good generalization without overfitting.

Further, Fig 7(b) presents the F1 score for both training and validation sets, which combines precision and recall into a single metric. Here, Fig. 7(c) represents the Area Under the ROC Curve (AUC) for training and validation sets that measure the model's ability to distinguish between classes. Higher AUC values close to 1 indicate excellent performance of the model. Finally, Fig. 7(d), displays the Training and Validation Loss, which is decreasing, and represents that the model is learning effectively and is not overfitted.

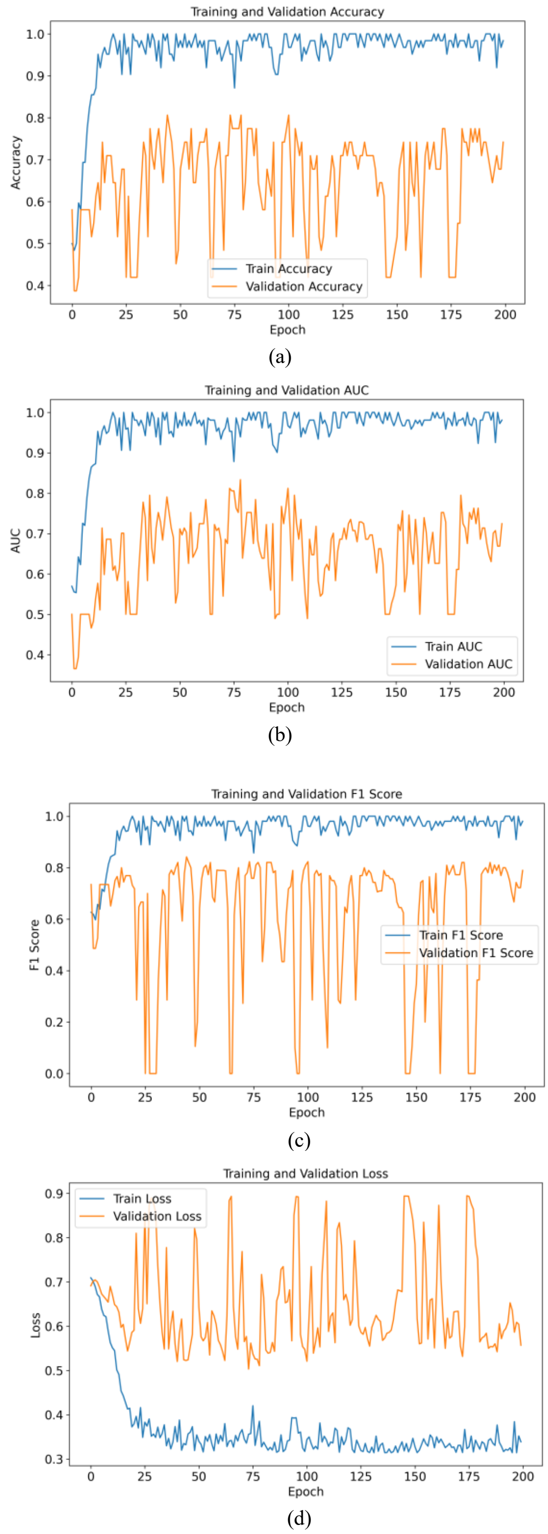

Fig. 7. Performance Analysis of Training and Validation (a) Accuracy (b) AUC (c) F1-Score (d) Loss

A. Output

For the GCN model, we achieved a test accuracy of 0.8552 and an F1 score of 0.8550. Using the GNN model with Differential Pooling, we obtained a test accuracy of 0.7873 and an F1 score of 0.8112. After implementing the GAT (Graph Attention Network), we recorded an accuracy of 0.8371 and an F1 score of 0.8500. The performance of the GCN model is slightly better. A comparison of all three models is provided in Table II.

TABLE II. RESULTS

	Test Accuracy	F1 score	Auc
GCN	0.8552	0.8550	0.8564
GNN	0.7964	0.7805	0.7984
GAT	0.8371	0.8500	0.8356
GCN (Dou et al. (2021))	0.8371	0.8286	-
GNN (Dou et al. (2021))	0.7692	0.7773	-

Fig. 8 and 9 illustrates the visualization of the proposed GCN model applied to testing (unseen) data. The results indicate that the proposed methods are effective in distinguishing networks associated with real versus fake news. The figure shows embeddings before and after training, each representing the embedding of one news/graph in the test set. The darker the color, the larger the numeric value.

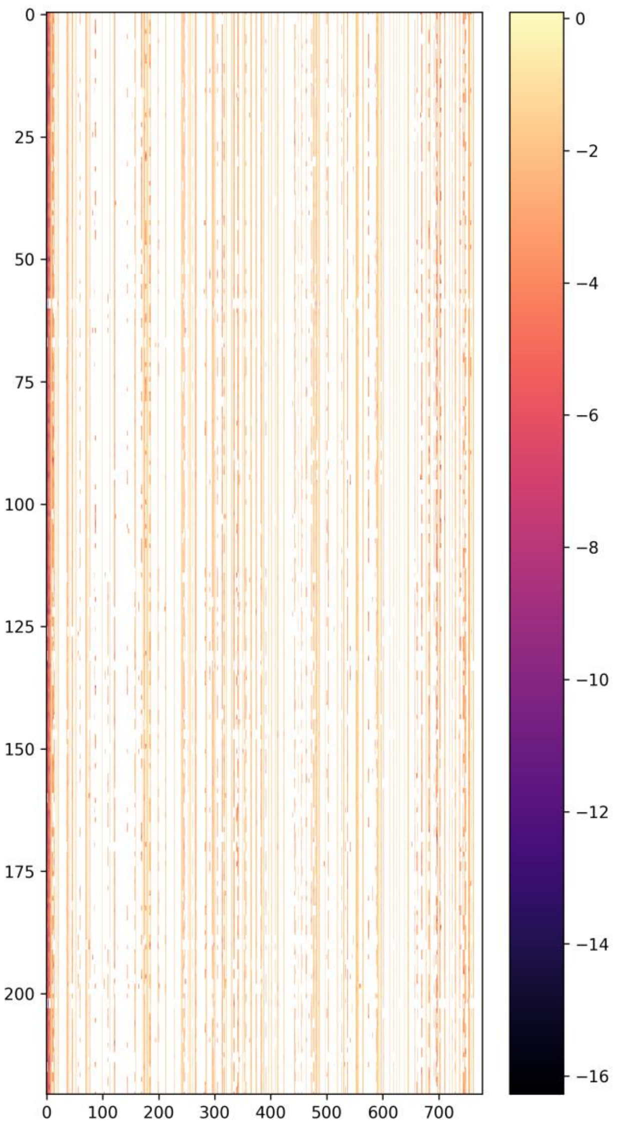

Fig. 8. Data before the application of the proposed model

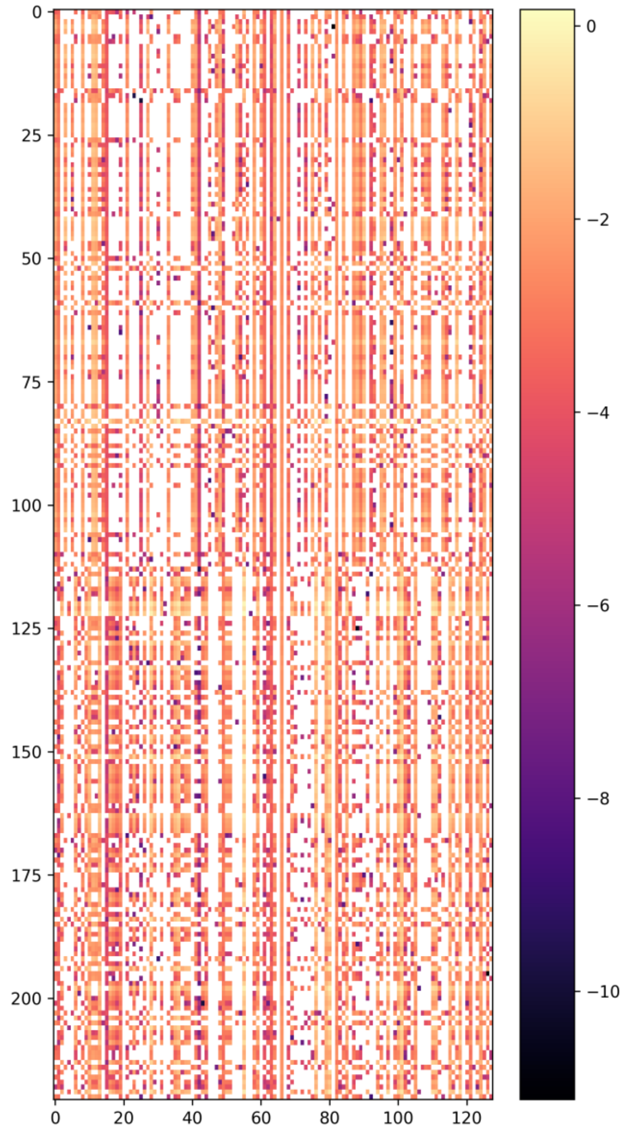

Fig. 9. Data after the application of the proposed model

V. CONCLUSION

This project has far-reaching practical implications. As shown in the results, the GNN models have a high potential to quickly and correctly identify fake news, which can be a good improvement in the already existing manual human-fact checker.

Also, with the rise of AI including ChatGPT, BlackboxAI, Gemini, etc., a lot of fake news fabricated with more nuances, in the form of images is being circulated worldwide. Today AI is so efficient that it can efficiently generate images of people that don't even exist. This causes great confusion with respect to the credibility of sources and can lead to a lack of trust among users. In [18], Dou et al. have applied the GCN and GNN-DP models for User Preference-Aware Fake news Detection. The results obtained with the proposed model are compared with the results of Dou et al. and are included in Table II. As is clearly visible in Table II, with some hypertuning, the results obtained from our prediction are much better than that of the prediction done by Dou et al. (2021). The project also drives advances in AI and machine learning, particularly in techniques like GNN with DiffPool, fostering further academic research into misinformation dynamics. While doing the project, several design choices were made to achieve the desired result. The future aspects include more fine-tuning of the hyperparameters and making some improvements in the model, to achieve better results. Secondly, GNNDP, although an expressive method that could have given good results with its hierarchical pooling, was not used properly. As we can analyze from Fig. 6, the graphs are relatively small, shallow, or without clear local neighborhood boundaries. So, to improve that, we can use GNN-DP for a larger dataset. Finally, although the current approach uses undirected graphs for modeling, exploring niche models that excel with directed graphs could yield even higher performance in future research.

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