Abstract—Detection of fake news is crucial to ensure the authenticity of information and maintain the news ecosystem’s reliability. Recently, there has been an increase in fake news content due to the recent proliferation of social media and fake content generation techniques such as Deep-Fake. The majority of the existing modalities of fake news detection focus on content-based approaches. However, most of these techniques fail to deal with ultra-realistic synthesized media produced by generative models. Our recent studies find that the propagation characteristics of authentic and fake news are distinguishable, irrespective of their modalities. In this regard, we have investigated the auxiliary information based on social context to detect fake news. This paper has analyzed the social context of fake news detection with a hybrid graph neural network-based approach. This hybrid model is based on integrating a graph neural network on the propagation of news and bi-directional encoder representations from the transformers model on news content to learn the text features. Thus this proposed approach learns the content as well as the context features and hence able to outperform the baseline models with an f1-score of 0.91 on Politifact and 0.93 on the Gossipcop dataset, respectively.

I. INTRODUCTION

Social platforms like Facebook and Twitter are becoming increasingly popular for day-to-day news consumption due to ease of access, low cost, and fast news dissemination [1]. As a result, these platforms have increasingly become the dominant source of information. However, the authenticity of news on these platforms is suspicious without any regulatory mechanism. Hence, social media also enable the wide propagation of fake news, implanted with false information. False or misleading information, commonly known as fake news, can cause significant damage to individuals and society. A series of recent incidents have demonstrated the potential of fake news in damaging personal, economic and national integrity. For example, a recent rumor caused the death of 800 people after the consummation of alcohol-based cleaning products as a cure for Covid-19 [2], and the influence of fake news in the democratic process of a country [3]. Looking at these consequences of fake news, many organizations have considered it a global challenge.

Fake news can be classified as parody, satire, fabricated news, propaganda, etc. [4]. Moreover, the term also confine the concepts of disinformation (intentionally misleading information), misinformation (information that can be proven to be false), manipulation, and rumors [5]. Although many definitions of fake news exist, there is no universally accepted one. One generalized definition of fake news introduced in literature [6] is “fake news is intentionally and verifiably false news published by a news outlet.”

Traditional sources of media such as television and newspapers have a structure of one-to-many. However, with its millions of monthly active users, social platforms such as Twitter are examples of a many-to-many approach. Therefore, surveillance of information diffused in such platforms is relatively complicated. Moreover, news on social platforms is emerging unprecedented, making it increasingly difficult to fact-check. Many fact-checking websites such as Snopes [7], and Politifact [8] exist to combat the problem of fake news. However, most of these are purely on manual methods and are difficult to scale up. Therefore, researchers are now focusing on data-driven or machine learning-based approaches to automatically and accurately detect fake news. Most of these approaches are based on user and content-based features, which are insufficient to address state-of-art generative modalities. However, a recent study shows that the propagation characteristics of news vary based on their nature, irrespective of their content properties [9]. Therefore, features corresponding to the propagation patterns of news could be effectively used as a basis for fake news detection on social media [10] [11] [12]. Propagation patterns are useful in incorporating the context of social influence, but in contrast to content-based features, the features have the advantage of being language and content-agnostic.

This paper explores a method of constructing the propagation graph of the social media network, following the propagation structure of Twitter posts. We then explored the graph neural network-based representation learning algorithm to extract the propagation features from the structured graph automatically. A hybrid model is built that exploits both the context features extracted with the graph neural network and the content features with the transformer model and embeds both the textual and structural information into a high-level abstract representation that can be effective for better analysis of the propagated tweet in a social network. We empirically evaluate our proposed model on two public datasets from Twitter, Politifact, and Gossipcop. The proposed model is compared with the baseline models on multiple evaluation indicators such as Accuracy, Precision, Recall, F1-score, and...
AUC. Moreover, we have also analyzed and compared the performance of the proposed model with the model based on manually extracted propagation characteristics of news for characterization of its authenticity. The details of the proposed approach are discussed in the following sections.

II. BACKGROUND AND RELATED WORK

Fake news detection has gotten much attention in recent years as a research subject. The existing approaches of fake news detection in the literature typically are of three types (Shu et al. (2017)) [13], namely news-based, user-based and propagation-based, which are based on the use of different types of information available in the social media. Moreover, news-based approaches fall into the category of content-based approaches, whereas the other two approaches lead to context-based. Content-based and Context-based approaches merged are also getting popular nowadays for effective detection of propagation of fake news, which is also called the mixed approach [12].

Content-based approaches attempt to solve the problem of fake news classification by using the news article’s headline and body: hence it is called content-based. The underlying idea of this kind of approach is that fake news exhibit a significantly different presentation style than real news. In a work presented by Perez et al. [14], different text-based content features, namely, Ngrams, Punctuation, Psycholinguistics features, readability, and syntax, are extracted from the text of the news. The linear SVM model was trained on such features. In another work presented by Horne et al. [15], similar feature engineering was applied but considered satire as one of the classes along with fake and real. In work proposed by Nor et al. [16], weak labeling was utilized, where labeling of news articles was done based on which category their source belonged to. The considered features extracted from the news content are Style, Complexity, Bias, Affect, Moral, and Event. Wang et al. [17] experimented on the Politifact dataset and used six unique labels for the target variable. Traditional ML algorithms were trained mainly focusing on neural nets, which provided promising results over all the considered models.

Context-based approaches mainly rely on propagation patterns of news on social media networks (e.g., Twitter) to classify news articles. Propagation patterns are constructed by considering interactions between tweets and users’ following, retweets, and likes. In work proposed by Wu et al. [18], a hybrid kernel function based on a random walk graph kernel and an RBF kernel using propagation features was proposed to model the propagation behavior of fake news. Fake news spreads can be easily modeled as graphs on social media platforms, and Graph Neural Networks recently have been popular for automatically extracting propagation features of graphs and designing better models for fake news detection [10], [11], [19], [20]. Propagation patterns have the distinct advantage of being language and content-agnostic. Comparatively limited studies [10] [11] [12] have been found in leveraging propagation features for detection of fake news. The graph classification approach aims to optimize the use of propagation features, and the success of graph neural network approaches in the prior works [10], [21], [21], [22] motivates further investigation of the graph neural network model for characterization of fake news.

Mixed approaches are getting the most attention nowadays to combat the limitations of both content and context-based approaches by combining their advantages. The mixed approach uses both propagation pattern and content, usually in the text, to verify the validity of news articles. Ruchansky et al. [23] proposed a model consisting of multiple components to extract representations of articles and to extract representations of users. Both these components are then integrated to get a resultant vector to be used for the final classification task. Kai et al. [24] proposed a framework consisting of five components: a semi-supervised classification component, a publisher-news relation embedding component, a user embedding component, a news content embedding component, and a user-news interaction embedding component. The latent representations for news content and users are learned via non-negative matrix factorization, and the problem is then formalised as an optimization over the above components. In work proposed by Nguyen et al. [25], a propagation graph was built using news sources, news articles, social users, and interactions between two entities at a given time. Additionally, the stance of the tweet with respect to the news title was also taken into account. Bi-directional LSTM (Bi-LSTM) was used to optimize the fake news detection objective. The approach emphasizes learning generalization representations for social entities by optimizing three concurrent losses, namely, Stance loss, Proximity loss, and Fake News Detection Loss.

III. DATASET DESCRIPTION AND PRE-PROCESSING

In this work, we have used a public data repository, FaKeNewsNet [26]. The repository consists of comprehensive datasets from two popular fact-checking websites, Politifact and GossipCop. The datasets include social context, news content, and other dynamic information for the fact-checking websites. Politifact [8] project is based on U.S. politics that reports on accuracy of statements made by elected officials,
their staffs, lobbyists, candidates, interest groups and many others involved in. Whereas, GossipCop [27] website fact-checks celebrity reporting. Both datasets have a number of articles whose ground truth is provided by its source (i.e. assigned by independent journalists). The word clouds representations of both the types of news are provided in Figure 1.

A. Data Collection and Pre-preprocessing

We extracted the available information of the news based on the approach mentioned in work [26]: news body, tweets, retweets and user profiles, that is relevant to tweet ids for every news article in the datasets. For every news article in the dataset relevant tweet ids are available. However, we discarded the news articles with missing text content. Some statistics of the collected datasets are provided in Table I.

|             | Politifact |             | Gossipcop |             |
|-------------|------------|-------------|-----------|-------------|
|             | Fake       | Real        | Fake      | Real        |
| News Articles | 432        | 624         | 5323      | 16817       |
| Tweets      | 164,892    | 399,237     | 519,581   | 876,967     |
| Unique Users | 201,748    | 596,435     | 504,638   | 199,031     |

B. Propagation Graph Construction

For every news article in the dataset, Twitter API was used to retrieve its Tweets and Retweets. Propagation graph is then constructed to model how information disseminates from one user to another. However, Twitter API does not provide an immediate source of a retweet. For example, tweet0 has been retweeted in retweet1. If retweet1 is retweeted again in retweet2, twitter would store tweet0 as source of both retweets. In order to determine the immediate source of a retweet, all tweets and retweets in the given set are sorted based on timestamp. Let \{tweet0, retweet1, retweet2 ...\} be a set of sorted tweets and retweets. For each retweeti, its immediate source is searched from tweets/retweets in the same set which were published earlier using the following heuristics,

1) retweetj is identified as source of retweeti if owner of retweetj mentions owner of retweeti.
2) Or if retweeti4 is published within a certain period of time after retweetj.
3) Else tweet0 is considered as source of retweeti.

Following the above mentioned heuristics return an information cascade for tweet. All such cascades are connected to the source news node to construct a propagation graph of the news articles as shown in Figure 2. Followers/Following information is not considered in construction of propagation graphs due to the strict Twitter API rate limits which would limit their availability at inference time.

C. Feature Engineering

Feature extraction performed in this work is divided into two parts - node-level and graph-level.

1) Node-level features: Each node in the propagation graph is either a tweet or retweet with a corresponding user. Node-level features are usually extracted on the basis of its characteristics and neighborhood. Different node level features are considered including user-based, text-based and temporal as mentioned in Table II. User-based features are basically the characteristics of author of node, which includes verified status, number of followers and number of friends. Friends in twitter terminology are accounts that a user follows. Text-based features are extracted from text content of the node (tweet/retweet) and try to capture the sentiment of the tweet. These include number of hastags, number of users mentioned, sentiment score using VADER [28] and frequency of positive and negative words. The temporal features we collected include difference in publication time with source node, parent and neighbors, which take into account the timeline of the node and its neighbors.

2) Graph-level features: A simple approach to extract a vector representation of a propagation graph would be applying aggregation techniques (averaging, max, min) on handcrafted node-level features [11]. In this paper, we have used simple averaging of node-level features along with meta information of graph as proposed by Meyers et. al. [11] as a baseline. We start with collection of basic statistics at graph-level - number of nodes, number of tweets and number of users. Next, mean aggregation is used to incorporate node-
TABLE II: Node-level features

| Feature Class | Feature Name |
|---------------|--------------|
| User Based    | Is verified user |
|               | Number of Friends |
|               | Number of Followers |
| Text Based    | Number of Hashtags |
|               | Number of mentions |
|               | Sentiment score computed using VADER |
|               | Frequency of positive words |
| Temporal      | Frequency of negative words |
|               | User account timestamp |
|               | Time difference with source node |
|               | Time difference with immediate predecessor |
|               | Average time difference with the immediate successors |

level information such as average number of friends, followers, retweets per tweets and time between tweet and its retweets. Finally, we collect temporal features such as total amount of time news article of referenced on twitter which is essentially the difference between the publication time of first and the last tweet, number of users involved in propagation after 10 hours of news publication and percentage of tweets/retweets published in first 60 minutes. Table III shows different graph-level features collected.

TABLE III: Graph-level Features

| Feature                        | Description                                                                 |
|--------------------------------|-----------------------------------------------------------------------------|
| num_nodes                      | Total number of tweets and retweets for a news article                      |
| num_tweets                     | Number of tweets                                                           |
| avg_num_retweets               | Average number of retweets per tweet                                        |
| retweet_perc                   | Average number of retweets per tweet                                        |
| num_users                      | Number of unique users                                                      |
| total_propagation_time         | Amount of time news was referenced on twitter                              |
| avg_num_followers              | Number of followers averaged over all users                                 |
| avg_num_friends                | Number of friends averaged over all users                                   |
| perc_tweet_1_hour             | Percentage of tweets in first hour of news publish time                     |
| users_10h                      | Users reached in 10 hours                                                   |
| avg_time_diff                  | Avg. time between a tweet and its retweet                                   |

IV. METHODOLOGY

Our proposed methodology incorporates basically three modules: (a) Graph Neural Network for modelling propagation context of news, (b) Pretrained Transformer model to learn from the news content, and (c) finally a mixed module to combine the representation of the above two modules.

A. Graph Neural Network for modelling propagation pattern

Graph Neural Networks (GNN) are a class of neural networks that operate directly on graph structures. Social media platforms, like twitter, can be modelled as graphs, as shown in Figure 2. GNN works on the principle of message passing or neighborhood aggregation which is a iterative process to generate node embeddings by aggregating information from local neighborhood. Consider a graph $G = (V, E)$ with a corresponding node feature matrix $X \in \mathbb{R}^{d \times |V|}$ and adjacency matrix $A \in \{0, 1\}^{V \times V}$. After $k$ iterations of message-passing, the node embeddings can be represented by,

$$H^{(k)} = f(A, H^{(k-1)}; W^{(k)})$$

where $H^{(k)}$ is node embedding matrix or output of GNN after $k$ iterations, $f$ is message passing function with trainable parameters $W^{(k)}$. GNNs aggregate the neighbourhood representation within $k$ hops and then apply a pooling such as $\text{SUM}$, $\text{MEAN}$, $\text{MAX}$ to obtain the final representation of the node. The representation which incorporates the social context information can then be used to classify the graphs. The general steps involved in training of GNN involves:

1) Generate node embeddings using multiple iterations of message passing
2) Extract graph embedding by aggregation of node embedding
3) Feed the embeddings into fully-connected layers for classification

Our work is based on building on the apparent potential of abstract features extracted by GNN on propagation network of twitter to detect fake news. The working principle can be defined as: Given a news propagation graph $G$ of a specific news item, that consists of a sets of tweets and retweets, how significant the propagation features are at classifying the news $G$ as fake or real. We applied here few most recent networks of GNN, namely GCNConv [29], GATConv [30] and GraphConv [31] for modelling propagation behaviours of fake news. The details of each of model are discussed below:

**GCNConv:** GCNConv [29] is a graph-based semi-supervised learning algorithm outlined in which the learner is provided with an adjacency matrix, $A$, and node features, $X$, as input and a subset of node labels, $Y$, for training. GCN is spectral based, where eigen-decomposition of the graph Laplacian is used in network propagation. This spectral method is used to aggregate neighboring nodes in a graph to infer the value of the current node. In GCNConv, eigen-decomposition is performed via approximation to reduce runtime. The propagation rule of GCNConv, can be represented by the following equation:

$$X' = \hat{D}^{-1/2} \hat{A} \hat{D}^{-1/2} X \Theta,$$  

where, $\hat{A} = A + I$ indicates the adjacency matrix with self-loops for every nodes, $X'$ is intermediate node embedding matrix or output after applying message passing function on embedding $X$ with layer specific trainable parameters $\Theta$, $D$ is the degree matrix to normalise large degree nodes. $D_{ii} = \sum_j A_{i,j}$ is the corresponding diagonal degree matrix that acts as a normaliser to circumvent numerical instabilities. The adjacency matrix $A$ consists of edge weights via the optional edge_weight tensor. The node-wise formulation is provided below:

$$x_i' = \Theta^T \sum_{j \in N(i) \cup \{i\}} \frac{e_{j,i}}{\sqrt{d_j d_i}} x_j$$

where, $N(v)$ is the neighboring nodes of node $i$, $d_i = 1 + \sum_{j \in N(i)} e_{j,i}$, where $e_{j,i}$ denotes the edge weight from source node $j$ to target node $i$.

**GraphConv:** GraphConv [31] is a generalization of graph neural networks capable of taking into account higher order
graph structures at multiple scales. The message passing function for GraphConv is given by,

$$x'_i = \Theta_1 x_i + \sum_{j \in N(i)} \Theta_2 e_{j,i} \cdot x_j$$  \hspace{1cm} (4)

where $e_{j,i}$ denotes the edge weight from source node $j$ to target node $i$.

GATConv: GATConv [30] is a attention-based graph neural network algorithm. It is an extension of GCNConv where instead of assigning same weight to each neighboring node, different weights are assigned through attention coefficients. This is achieved without use of expensive matrix calculations or prior knowledge of graph structure as provided below:

$$x'_i = \alpha_{i,i} \Theta x_i + \sum_{j \in N(i)} \alpha_{i,j} \Theta x_j$$ \hspace{1cm} (5)

where the attention coefficients $\alpha_{i,j}$ are computed as

$$\alpha_{i,j} = \frac{\exp(\text{LeakyReLU}(e_{ij}))}{\sum_{k \in N(i) \cup \{i\}} \exp(\text{LeakyReLU}(e_{ij}))}$$ \hspace{1cm} (6)

Where, $e_{ij}$ denotes the importance of node $j$’s features to node $i$, and $N$ is the Neighbourhood of node $i$.

B. News content representation

Text content of a news article can provide important signals in distinguishing fake and real news. We adopt two approaches...
to get vector representation of text content, Doc2Vec [32] and Embeddings from pretrained transformer models [33]. Doc2Vec is an unsupervised algorithm and extension of Word2Vec [34] that computes vector representation of variable length documents. The difference between Word2Vec and Doc2Vec is the addition of a special token called Document ID which learns the vector representation of entire document. Another approach that we considered for encoding text content was making use of pretrained transformer models from sentence-transformers library [33]. Specifically, we considered (1) all-MiniLM-L12-v2 based on [35] (2) all-distilroberta-v1 based on distilled version of [36] (3) all-mpnet-base-v2 based on [37]. Transformer networks output an embedding for each token in the input text which are then averaged to obtain fixed length embedding for the document. Since all the models that we considered had a maximum sequence length of 512 tokens (500 English words), we consider different parts of text as input when length of text is greater than 512 tokens. Specifically, we consider first 512 tokens, last 512 tokens and combination of first 256 and last 256 tokens.

C. Mixed Approach: Combine context and content features

Research on multi-modal fusion has shown that models trained by combining data from multiple sources have a clear advantage over those trained using only one source [38], [39]. In our research we explore two fusion techniques to combine the content and context features - Early fusion and Late fusion. The mixed approach takes the benefits of both the modalities and hence can be assumed to be more effective. Early fusion based mixed approach is shown in Figure 3 involves concatenating vector representations of text content and propagation to be used as input to fully connected layers for classification. Dimensions of both modalities are reduced to 32 to prevent one modality from overwhelming the other modality. Conversely, Late fusion outputs final prediction by aggregating predictions from base-classifiers. We explore aggregation strategies for late fusion - mean and classifier-based. In Late Fusion mean approach, predictions from aggregated using simple while in classifier approach a meta-classifiers is trained on out-of-fold predictions of base-classifiers. Figure 3 also illustrates the late fusion architecture of our approach.

V. EXPERIMENTAL RESULTS AND ANALYSIS

The experiments were conducted on Google Colab Pro with 25 GB RAM and the codes were developed using python 3. Different libraries are used for the experimentation are Pytorch-Geometric [40], sklearn [41], sentence-transformers [33], Gensim [42], and Pandas [43]. The classification metrics used are Accuracy, F1-score, Precision, Recall.

Dataset preparation (splitting and sampling) details for modelling are provided in Table IV. For Politifact, the train-test dataset ratio was kept at 4:1. For training of models, 90% of samples are randomly selected for training from train dataset and remaining are used for validation. This process is repeated for 10 times and average of the considered evaluation metrics are reported. This strategy is used because of small size of Politifact dataset. For GossipCop, the dataset is split into train-test-val in ratio of 70:15:15. Cross validation is not used for GossipCop because of large size of dataset. In case of Late fusion classifier, 3-fold inner cross validation(CV) is used to generate out-of-fold predictions. Splitting of dataset is done in a stratified manner such that ratio of fake to real news remains same in all sets. Same splits are used for all experiments to ensure consistency and fair estimate of performance. Wherever applicable, each model is trained for maximum of 50 epochs and best model weights are selected from epoch with lowest validation loss. Learning is set to 0.001 and batch size of 64 is used.

|               | Politifact | GossipCop |
|---------------|------------|-----------|
| Train-Test split | 80:20      | 85:15     |
| Train-Val split | 10-fold CV | 82.35:17.65 |
| Sampling      | Random over sampling | None     |
| Class Weights | None       | Uniform   |

For the purpose of classification using graph-level features, we experimented with traditional machine learning algorithms such as ensemble methods, logistic regression and stochastic gradient descent. Specifically, following algorithms are considered - PassiveAggressiveClassifier, RidgeClassifier, LogisticRegression, SGDClassifier, ExtraTreesClassifier and RandomForestClassifier. The performance of different classifiers using graph-level features on Politifact and GossipCop is illustrated in Table V.

We performed comprehensive experiments on the considered dataset to gauge effectiveness of different modalities (Text features and context features) in classification of fake news. Four sets of experimentation are performed as provided below:

1) Classification based on manually extracted Graph-level features
2) Automatic Graph-level classification (GNNs directly applied on propagation graph of news)
3) Classification based on Content (i.e Text) features of news
4) Mixed model classification, i.e. combination of both text based and propagation based features

Classifiers could not perform that well on Politifact with RandomForestClassifier reaching maximum f1-score of 0.48. The likely reason for this is the small size of Politifact dataset which does not allow for learning of meaningful patterns. However, a decent f1-score of 0.88 is reached on GossipCop dataset. In both cases, RandomForestClassifier performs best closely followed by ExtraTreesClassifier.

Using Graph Neural Networks, we achieve a maximum f1-score of 0.79 on Politifact with GCNConv and 0.907 on GossipCop with GraphConv. We experimented with different number of layers and embeddings size for convolutional and found that 4 layers and 64 dimensions provides comparable results to other settings while having a shorter training time. Results are shown in Table VI.

Text content of a news article provide important signals in distinguishing fake and real news. The results on this modality...
An improvement of 3% is achieved over best performing baseline text and GNN models when using GossipCop dataset. All fusion techniques achieved significant improvements over unimodal models (text and GNN), as shown in Table VIII.

In this work, we explored a method of detecting fake news based on its propagation characteristics on social media and its content. Experiments were performed to demonstrate that using both content and propagation characteristics provides better performance than relying on a single modality. Fake news detection will be most beneficial when fake news can be detected at early stages of propagation.

VI. CONCLUSION AND FUTURE SCOPE

In this work, we explored a method of detecting fake news based on its propagation characteristics on social media and its content. Experiments were performed to demonstrate that using both content and propagation characteristics provides better performance than relying on a single modality. Fake news detection will be most beneficial when fake news can be detected at early stages of propagation.
identified at an early propagation stage. GNN approaches that can learn on structured data like graphs seem to be promising for investigating such directions. Moreover, most past approaches used in fake news detection are not interpretable. Hence, exploring the proposed model for interpretation and explanation of the achieved results can be another future direction of our research.

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