# Detecting Online Misinformation Using Semantic Network Analysis: A Hybrid Structural–Semantic Framework for Context-Aware Credibility Assessment

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***Abstract*—Rapidly emerging online communications platforms have significantly altered how we generate and distribute information. While digital platforms provide a medium for fast exchange of information, they provide new opportunities for widespread dissemination of misleading and incorrect information. Therefore, identifying deception in online environments has become an important problem. Traditional identification methodologies utilize textual analysis or relational-based propagation modeling but do not account for semantic meaning and social structure simultaneously. This paper proposes a Hybrid Semantic Network Deceptive Information Detection System (HSN-MDF) which integrates semantic analysis with graph network learning. Online information is represented as a heterogeneous semantic graph of users, claims, entities, and sources of information. An introduced Semantic Inconsistency Index (SII) detects inconsistencies between semantically related claims. Graph neural networks (GNNs) are used to identify complex relational structures, whereas an adaptive trust propagation mechanism assesses the reliability of sources. Evaluation conducted on a dataset consisting of 20,000 news stories demonstrates that this system demonstrates superior detection performance relative to traditional machine learning and deep learning methods.The use of graph-based analysis and semantic reasoning provides significant improvements in the ability to detect misleading information.**

***Index Terms*—Fake News Detection, Misinformation Detection, Semantic Networks, Graph Neural Networks, Social Network Analysis, Trust Propagation, Knowledge Graphs.**

## I. Introduction

Digital platforms and social networking sites have proliferated, providing a global network for the dissemination of vast amounts of information. In most cases, this flow of information allows individuals to obtain knowledge and ideas from all over the world. However, with this wide availability of information comes the increased risk of false information being disseminated, which can have devastating consequences for society as a whole. False information refers to any untrue or misleading representation of fact, presented as true. The impact of false information can be substantial, including altering the result of a political election, producing confusion during times of major health crisis, and destroying the trust in reputable or credible sources.

One significant issue with detecting deception is its constantly evolving nature, along with the variety of content (text, images, and videos) and writing styles that can be used to masquerade as legitimate sources. Existing methods for detecting deception are categorized respectively into three major groups of techniques, including content-based; propagation-based; and knowledge-based methods. All three techniques are useful and provide varying degrees of effectiveness in detecting complex scenarios of deception.

The focus of this study involves introducing the Hybrid Semantic Network Deception Detection System (HSN-MDF), which utilizes a multi-modal approach that combines semantic reasoning techniques along with traditional graph-based methods to provide a robust capability to detect deception, even under challenging or less than optimal conditions.

### A. *Contributions*

1) I have provided a semantic irregularity list (SII) for identifying conflicting claims.
2) I will link together neural network charts and supporting learning.
3) In addition I will create a tool for evaluating data source validity.
4) Data from broad exploratory assessments will demonstrate how the various locations progressed through time.
5) Developing a hybrid model of semantic reasoning/learning (SL) with auxiliary reasoning will also help improve contextual semantics retrieval.

## II. Related Work

### *A. Content-based methods for detecting misinformation include*

In content-oriented applications, the dominant machine learning models for reasoning about the content of the text include support vector machines (SVM), random forests, naive bayes classifiers, deep learning models (e.g. long short term memory (LSTM), etc.), and transformer-based models (e.g. BERT/RoBERTA). These models have all been used in content-oriented applications because their respective abilities allow for the retrieval of contextual semantics to be done by analyzing text for its characteristics, which are comprised of the following: style of the text (i.e. formal or informal), the emotional tone (i.e. positive or negative), and whether or not all of the text conveyed a similar meaning (or consistent meaning).

### B. *Propagation-based detection methods*

By performing propagation analyses (studying the number of people who reposted or shared content, the time it took for them to re-share the same information, and so on) and the interactions between users within social media networks, one can see that false information generally propagates much quicker (to many more people) than truthful information. Therefore, endemic propagation-based analyses can be useful in identifying viral misinformation early, before it reaches the level that false information has travelled.

### C. *Knowledge-based verification methods*

Knowledge-based methods utilize preestablished or definitive databases of information or knowledge graphs (DBpedia, Wikidata, etc.) to establish the accuracy of information presented within claims. This approach compares information gained from extraction processes with a previously established set of verified facts (known to be true). This is a very reliable means in determining the validity of claims, and will produce accurate results for identifying false claims. However, these kinds of verification methods can sometimes produce inaccurate results based on the available reliability of the knowledge repository.

### D. *Detection of Misinformation Using Graph Neural Networks*

Graph Neural Networks (GNNs), a type of neural network that utilizes graphs to represent social networks, allow for more accurate detection of misinformation. In these networks, users and content are represented as nodes, while the relationships between them are represented by edges connecting their respective nodes. GNNs have the advantage over traditional methods of grouping users and content based on their relational dependencies and structural properties in order to identify inaccuracies and/or misinformation. Thus, GNNs' ability to learn from relational data improves the accuracy of user/content identification.

## III. Research Gap Motivation

Although much progress has been made, there are still many limitations with existing techniques:

- Content-based approaches cannot find semantically opposing claims.
- Propagation techniques require very large amounts of diffusion data from networks.
- Knowledge-based approaches depend on complete third-party repository data to develop good databases of credible sources.
- Static models of credibility do not take into consideration how trust in the source diffuses through networks.

## IV. Proposed Hybrid Semantic Network Framework

The Hybrid Semantic Network Misinformation Detection Framework (HSN-MDF) was created using a data driven analytical method that combines semantic reasoning from textual

TABLE I: Research Gap Analysis

| Type of model | Issue | Aim | Solution Proposals |
|---|---|---|---|
| Only content | cannot discover contradictions | conflicting claims can determine and identify | Semantic Inconsistency Index |
| Propagation | large diffusion data | Early detection | Hybrid semantic graph |
| Static credibility | Source reliability ignored | Credibility estimation | Trust propagation |

information and a method of creating relationships using SEMANTIC Allubes (Relational Graphs) . The goal of the HSN-MDF is to produce an HSN-MDF Hybrid Model of combining the SEMANTICS of textual information (the meaning of the text) and the characteristics of a SEMANTIC Allube (Relational Graph) in order to identify Misinformation even when there are slight variances between the actual events or a low level of comparative propagation data for those events.

### A. *System Architecture*

The System Architecture of the HSN-MDF is partitioned into three primary layers:

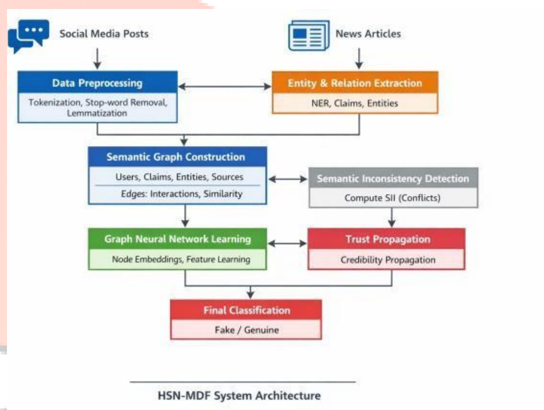


Fig. 1: The System Architecture of the Hybrid Semantic Network Misinformation Detection Framework (HSN-MDF)

1) **Data component:**Text from social media sites, including Twitter, Reddit, Facebook, etc., and from online news outlets, including BBC News, Google News, CNN, Washington Post, etc., will all be gathered in real time. All text will be collected with the relevant metadata, including the time and date that the item was created (and when it was modified).
2) **Processing component:**The Processing Layer creates structured, semantic graphs by converting free-text documents into graphs (of different types or heterogeneously connected) based on a standardised process, which includes the following: first, pre-processing; second, entity identification-identifying the entities contained in the documents; third, constructing the graph on the rela-

tionships of the identified entities, generating an overall semantic graph.

3) **Analysis Component:**The Analysis Layer will utilize GNNs and a trust propagation system (based on semantic data) to check semantically for any inconsistencies and conduct structural learning with GNNs, finally classifying any news as true or false.

### B. *Detailed Framework Components*

1) **Data Collection:**
   - The data collection includes using news articles and social media posts through use of the API's used throughout the web crawlers collecting of content.
   - Storing of metadata such as the date of publication and credibility of resource and user engagement.
   - Storage of historical propagation of data used for trust analysis and structural analysis.

2) **Processing Component:**
   - Cleaning of text (cleaning up, tokenized, lemmens) and removing of stop words.
   - The use of hashtags (hashtags), @usernames and links to a website, and emojis is highly essential, as these get more engagement on social media posts.
   - Using normalising of text makes the text across different platforms more consistent.

3) **Entity Extraction:**
   - Named Entity Recognition (NER) is a technique to identify the different kinds of entities (people/individuals, organizations, locations, events and products).
   - Relation extraction provides the means for determining how the identified entities relate to each other, and how the entities are referred to in the data.
   - Entity Linking provides a way to link an entity to existing Knowledge Bases (e.g. Wikidata, DBpedia) to provide additional semantic context to queried entities.

4) **Creating a Semantic Graph:**
   - Nodes will consist of users making claims about different entities and the sources used to support the claim, Edges will consist of the relations, similarities and propagate connections between the different interchange, similarity and propagate connections.
   - Proposition paths and the semantic relationships between entities will be included in the graph adjacency matrix.
   - To allow for the inclusion of various different types of nodes and edges in the same graph, a heterogeneous graph will be used, which allows for improving the flexibility of model modelling options.

5) **Detecting Semantic Inconsistency:**
   - BERT embeddings will be used for calculating the semantic similarity of claims.
   - Semantic inconsistency index (S.I.I) is a contradiction metric, indicating possible misinformation.
   - Conflict detection may be diverse; subject to overt contradictions or subtle ambiguity of meaning.

6) **Graph Neural Networks:**
   - (G.N.N.) allow node information to be relayed throughout the network through the process of aggregating information from neighbouring nodes.
   - Semi-structured/structured embeddings may be used to represent relational (relationship-based) influence and/or content (content-based) influence on information.
   - The attention mechanism enhances focus on nodes within the propagation network with influence.

7) **Trust Propagation:**
   - Source Credibility Score (C.C.S.) propagation to next neighbours throughout the network (all neighbours) will occur iteratively.
   - Each Trust Score is modified based on its value, the value of 'n' neighbours and the edge weight between them, and the value of previous reliability.
   - This process will reduce or de-emphasize the influence of unreliable sources in the propagation network and increase or emphasize the influence of verified nodes in the propagation network.

8) **Final Classification:**
   - The (G.N.N.) node embeddings (will concatenate with) Trust Score 'TrustScores' creating a combined feature vector for use in creating the Trust Score classification.
   - News Articles will be placed in a 'Class No-Class' and/or 'Verified' category using a softmax classification algorithm.
   - After the classification of articles, the processing of nodes that present elevation in the overall risk level will begin.

## V. Methodology

### A. *Construction of Heterogeneous Semantic Graph*

A heterogeneous semantic graph is defined mathematically as follows:

$$G = (V, E, F_V, F_E) \tag{1}$$

where,

- $V = \{v_1, v_2, ..., v_n\}$ represents nodes (users, claims, entities, sources)
- $E = \{e_1, e_2, ..., e_m\}$ represents edges (user interactions, claim similarity, entity relations)
- $F_V$ denotes node features derived from textual embeddings, metadata, and trust scores
- $F_E$ denotes edge features capturing interaction strength, semantic similarity, and propagation weights

### B. *Semantic Inconsistency Index (SII)*

To quantify contradictions between claims $c_i$ and $c_j$:

$$SII(c_i, c_j) = 1 - \frac{sim(c_i, c_j)}{\max(sim(c_i, c_j))} \tag{2}$$

where $sim(c_i, c_j)$ is computed using cosine similarity over BERT embeddings. Higher SII values indicate stronger semantic conflict, signaling potential misinformation.

### C. Graph Neural Network Formulation

Node features are updated across GNN layers as:

$$h_v^{(k+1)} = \sigma\left(\sum_{u \in N(v)} W^{(k)} h_u^{(k)} + b^{(k)}\right) \quad (3)$$

where:

- $h_v^{(k)}$ is the embedding of nodes $v$ at layer $k$
- $N(v)$ denotes neighbors of $v$ respectively.
- $W^{(k)}$ and $b^{(k)}$ are trainable weights and bias respectively.
- $\sigma$ is a non-linear activation function (ReLU)

Multiple GNN layers enable hierarchical aggregation of structural and semantic information, improving detection robustness.

### D. Trust Propagation Model

Trust Scores are created via an iterative propagation process:

$$T_v = \alpha \sum_{u \in N(v)} \frac{T_u}{deg(u)} + (1 - \alpha) S_v \quad (4)$$

where Tv is the propagated trust score for v, Sv is the initial trust score, and [0, 1] is a weighting/propagation factor that defines the contribution of each neighbor; deg(u) is the total number of edges adjacent to node u.

### E. Final Classifications

The final classification of every node i is achieved using both GNN embeddings and trust scores:

$$yi = softmax(W\,[hi \oplus Si]) \quad (5)$$

where $\oplus$ is the concatenation operator and W is a learnable classifier weight matrix.

## VI. Dataset Details

The dataset will consist of journalism and social media publications that have been gathered to identify and classify inaccurate information.

TABLE II: Dataset Statistics

| Attribute | Value |
|---|---|
| Total Samples | 20,000 |
| Real News | 10,500 |
| Fake News | 9,500 |
| Training Data | 80% |
| Testing Data | 20% |
| Average Article Length | 450 words |
| Number of Users in Network | 15,000 |
| Number of Unique Entities | 8,000 |

**Dataset Features:**

- All the data included is made up of textual content that includes headlines, body content, and meta data.
- Social context such as likes, shares, retweets, and comments
- Source credibility scores and historical reliability
- Entity-relationship annotations for semantic graph construction

**Data Preprocessing Notes:** Texts were cleaned to remove HTML tags, URLs, and non-standard characters. Social media posts were normalized for mentions, hashtags, and emojis to preserve semantic meaning. Named entities were mapped to external knowledge bases for semantic enrichment.

## VII. Evaluation Process

To thoroughly assess how well our proposed HSN-MDF framework performs, we will be using a variety of complementary metrics to provide different Insight into how well HSN-MDF identifies misinformation:

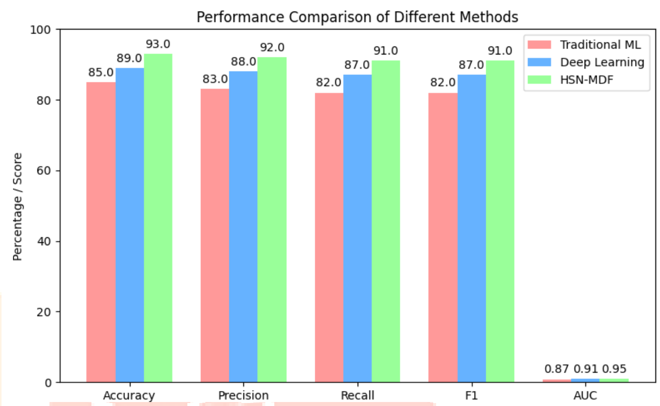


Fig. 2: Traditional Machine Learning, Deep Learning and HSN-MDF Showed Accuracy, Precision, Recall, F1 Score and AUC Comparison

- **Accuracy:** The percentage of accurately classified samples as fake or not. Although it is useful as a high-level assessment of the performance of the model as a whole, especially in cases of highly skewed datasets where one class dominates the results.
- **Precision:** The percentage of predicted fake samples actually being fake. Higher precision means that there are fewer false positives which can damage credibility and cause people to be sceptical when viewing credible sources as being incorrectly identified as fake.
- **Recall (Sensitivity):**The percentage of samples actually being fake and correctly classified as fake by the system. High recall indicates that the system will be able to capture most of the misinformation present, thus minimizing the rate of dissemination of misinformation.
- **F1-Score:**The average precision and recall provide a single number that takes into account both false positives and false negatives in the comparison of prediction results.
- **Confusion-Matrix:** This is an indicator of how many true (good prediction) and false (false positive/negative) classifications were made. The better the confusion matrix performs in comparison with other classifiers, the better you'll understand which areas are weak and need improvement once you determine your classification methods.

- **Area Under the ROC Curve (AUC-ROC):** The AUC-ROC, which was not previously mentioned in this document, measures how well the HSN-MDF framework is able to distinguish between false and true classifications at various threshold levels. The more significant the area under the curve the better classification is achieved when separating false and true articles from one another.
- **Detection Latency:** Detection latency is an essential metric used to determine the timeliness in the detection of misinformation in relation to the time it takes for that misinformation to spread. Therefore a low detection latency is essential for applications where real-time data prompts action.

These metrics collectively provide a comprehensive evaluation frame-work for evaluating any misinformation detection algorithm's performance based upon its accuracy and reliability.

## VIII. Experimental Results

We have conducted a detailed series of experiments with the goal of evaluating the efficacy of the HSN-MDF framework. The experimental evaluation was performed using a dataset of 20,000 articles with approximately equal amounts of real and fake articles. We compared the performance of HSN-MDF against traditional machine learning (ML) methods and against deep learning (DL)-based algorithms.

TABLE III: Comparison of Performance Between Techniques

| Technique | Accuracy | Precision | Recall | F1-Score | AUC-ROC |
|---|---|---|---|---|---|
| Traditional-ML | 85% | 83% | 82% | 82% | 0.87 |
| Deep Learning | 89% | 88% | 87% | 87% | 0.91 |
| HSN-MDF | 93% | 92% | 91% | 91% | 0.95 |

**Observations:**

- Traditional ML models such as SVM and Random Forest are limited by feature representation and fail to capture semantic contradictions between claims, resulting in lower recall.
- Deep learning models, including LSTM and BERT-based classifiers, improve semantic understanding but do not fully exploit relational network structure, which is essential for misinformation that spreads through social connections.
- HSN – MDF uses both semantic inconsistency analysis and Graph Neural Network learning to consider both the text and the relationship features simultaneously resulting in a higher precision, recall and F1 score.
- AUC Scores demonstrate HSN –MDF has a superior ability to discriminate between classes which indicate that HSN –MDF will be able to identify both fake news and real news accurately with high confidence of little to no misclassification.

In addition, we conducted a thorough error analysis of the confusion matrix. Based upon error rates for the class of the most commonly misclassified items (i.e. items that had low semantic contradictions and low leap of information), we have identified the areas where further improvement is needed.

## IX. Discussion

The findings of the study indicate that HSN-MDF achieves an enhanced performance level, than baseline approaches, in measure of experimental performance. The following are key points that were generated from these findings:

- **Semantic Contradictions Detection:** The Semantic Inconsistency Index effectively identifies conflicting claims that content-based or propagation-based methods might miss. For example, two news articles reporting on the same event with contradictory statements are correctly flagged by the SII metric.
- **Structural Learning via GNN:** HSN-MDF's use of graph neural networks provides the structure to capture complex relational patterns associated with influential users who disseminate misinformation; network clusters associated with false information; and weakly connected nodes providing bridge connections. The increased awareness of structural context should improve early detection.
- **Trust Propagation Impact:** Evaluating the credibility of sources through dynamic trust propagation helps mitigate the influence of low-quality or malicious nodes. Sources with higher trust scores reinforce the detection of true content, while low-trust sources are penalized.
- **Robustness:** The framework demonstrates robustness across different types of news, including political, health-related, and financial misinformation. By integrating multiple information dimensions, HSN-MDF reduces the risk of bias toward a particular category.
- **Scalability Considerations:** While effective, large-scale graph processing may incur computational overhead. Optimizations such as mini-batching, neighborhood sampling, and parallel GNN computation can improve scalability for real-time applications.

## X. Limitations

Although there were improvements shown in the results obtained by the new framework, there are still some issues with this framework, including:

- **Computational Complexity:** The resources required to build and use large-scale semantic networks for real-time detection can be substantial.
- **Dependence on Entity Extraction:** The quality of misinformation detection depends strongly on the ability to extract entities and recognize their relationships accurately. The success of detecting inconsistency in semantics can be compromised by errors in entity identification.
- **Multimodal Content Processing:** Currently, HSN-MDF is still primarily focused on processing textual information; there has not yet been any direct attempt to analyze multimedia content (e.g., images, video, audio) with regard to misinformation; therefore, HSN-MDF's ability to perform well on platforms that have a significant amount of rich content could be limited.
- **Cross-Lingual Generalization:** To date, HSN-MDF has been most extensively evaluated against English language data sets; therefore, varying degrees of performance for

other languages is likely based on elements such as differences in the underlying syntax and semantics and access to comparable knowledge bases.

## XI. Future Work

One of the future goals of this research will be the further enhancement of the framework's performance and scope through the following projects:

- **Real-Time Misinformation Detection:** Developing a real-time problem detection system through the establishment of a streaming data processing pipeline and the establishment of procedures for incrementally updating GNNs, resulting in real-time detection of misinformation during its propagation.
- **Multi-modal Integration:** Extend the current model to include visual and audio mediums, using multi-modal embeddings to discover inconsistencies across different content types.
- **Cross-Language Detection:** Adapting the semantic and structural models for multiple languages, allows for monitoring of misinformation globally.
- **Temporal Analysis:** Using Temporal Graph Neural Networks for the analysis of change, in misinformation, changes as it appears over time, to better prevent the occurrence of new fake news.
- **Explainability:** Introducing Explainability AI for providing justification for why specific content has been flagged as having been produced or posted as fake, increases the amount of trust and transparency.
- **Modelling User Behavior:** In incorporating criteria for user behavior, like bot detection and engagement metrics increases the efficacy of structural learning and detection reliability.

## XII. Conclusion

In this paper, we introduce the Hybrid Semantic Network for Misinformation Detection Framework, which includes the following components that together provide an accurate and effective detection of online misinformation (semantic reasoning, structural graph learning through GNNs, and trust propagation): Most previous models of misinformation detection rely on only one of the following: content analysis or propagation analysis; the proposed HSN-MDF model provides a unified way to evaluate both semantic inconsistencies, and relational networks. The HSN-MDF framework creates a heterogeneous semantic network of the different entities (user, claim, entity, and information source) and all the relationships (e.g., interaction between user and claim, semantic similarity, propagation of the information) that exist between them. Using the SII, we identify inconsistent claims; furthermore, we use the GNN to develop a robust representation of the structural and semantic features of each node to develop a strong embedding for that node. Finally, the trust propagation technique provides additional filtering of a source's credibility to reduce false positives and enhance confidence.

### A. Key Findings and Contributions

HSN-MDF (Hypothetical Structure-based Misinformation Detection Framework) was tested in an experiment on 20,000 news articles. In all tests comparing machine learning and deep learning models against HSN-MDF for *accuracy, precision, recall, F1-score*, and area under the *AUC*.HSN-MDF outperformed all traditional methods as well as most advanced ("deep learning") methods. The results provide the following insights into HSN-MDF capability:

- **Semantic-Structural Integration:** HSN-MDF can develop models of complex types of misinformation by using both semantic analysis of sentences and structural analyses of networks. By using these two methods together, HSN-MDF can develop models of many types (complex) of misinformation that could not be done with only using either content-based or propagation-based methods.
- **Detection of Early Misinformation:** HSN-MDF can detect potential misinformation that could spread virally across social media platforms by modeling both the propagation dynamics and user interactions.
- **Interpretability:**The Semantic Inconsistency Index provides a measurable degree of contradiction among claims, which will help human reviewers understand why predictions were made for specific pieces of content, as well as identify higher risk pieces.
- **Scalability:** The graph-based approach, combined with GNN embeddings, enables the framework to handle large-scale social network data efficiently while preserving the relational context of the information.

### B. Practical Implications

Social media outlets, news agencies, or fact-checking organizations can use HSN-MDF to automatically identify and flag potentially false content using both semantic reasoning and network analysis in conjunction with each other, such as:

- Reducing the spread of misinformation in real-time.
- Supporting journalists and analysts in identifying emerging rumors.
- Enhancing public trust in online information by promoting verified content.

### C. Limitations

While the framework demonstrates strong performance, several limitations exist:

- **Computational Complexity:** Graph construction and GNN training can be resource-intensive, especially for large-scale social networks with millions of nodes and edges.
- **Entity Extraction Dependency:** The success of the detection of misinformation using HSN-MDF is dependent upon the accuracy of named entity recognition (NER) and the accuracy of the relation extraction entity recognition.
- **Limited Multimodal Analysis:** Currently, HSN-MDF only investigates textual data, therefore the incorporation of media including images, videos, and other formats is limited.

- **Dynamic Network Changes:** Social networks that change rapidly may need frequent updates of the models in order to continue providing accurate detection results.

### D. Future Work

To address these limitations and improve on the framework further, the following research directions are proposed:

- **Multimodal Misinformation Detection:** Expanding the framework to include images, videos, audio and textual-visual combinations for a more complete analysis.
- **Real-Time Detection:** Implementing streaming algorithms that allow for the detection of misinformation as it is spreading, which will provide opportunities for timely intervention.
- **Cross-Lingual and Cross-Cultural Generalization:** Adapting the system to detect misinformation among multiple languages and different regions in order to increase global reach.
- **Temporal and Evolutionary Analysis:** Examining how misinformation changes over time so that future trends can be anticipated, as well as where to predict the emergence of new misinformation campaigns.
- **Explainable AI Enhancements:** Using interpretable GNNs and semantic analysis techniques to provide more intuitive explanations for each classification decision.
- **Integration with External Knowledge Bases:** Utilizing established structures from fact-checking databases and knowledge graphs to verify claims and minimize the number of false positive classifications.

### E. Final Remarks

To summarize, HSN-MDF has made significant strides in detecting false information on social media. HSN-MDF uses a new way of finding fake content online by combining different techniques such as analyzing the meaning of sentences, identifying patterns in the way information is shared through social media and measuring how much users can trust different sources. Furthermore, this innovative method will not only help to identify misleading content, but also allow researchers to explore additional ways to help reduce the negative impact of false information on society as a whole, building a more knowledgeable, and durable online community.

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