EXPLAINABLE MULTIMODAL AI FOR SENTIMENT AND INTEGRITY ANALYSIS IN DIGITAL JOURNALISM

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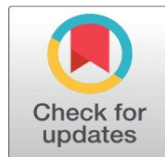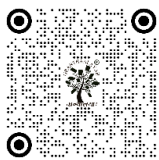[2] Assistant Professor, Department of Electronics and Telecommunication Engineering, Vishwakarma Institute of Technology, Pune, Maharashtra-411037, India
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ABSTRACT

The study attempts to deal with the increasing problem of the objective assessment of sentimental expression and narrative truth in broadcast media where editorial biases, sentimental manipulation, and narrative distortion may play a significant role in the species perception. Manual analysis is an aspect of traditional content analysis that has strong dependence on subjective judgment and is not scalable or consistent. The overall goal of the study is to establish an AI-based analytical tool that can objectively evaluate sentimental processes and confirm the logic of the narrative in the practice of the broadcast media. The offered methodology uses a multimodal AI framework with the combination of computer vision, speech processing, and natural language understanding. Transformer based attention mechanisms are used in combination with facial expression recognition, vocal prosody analysis and textual sentiment modeling to identify temporal sentimental patterns. The accuracy in narratives is assessed by use of semantic consistency analysis, event sequence modeling and alignment of facts across sources, which allow the detection of sentimental bias, exaggeration and informational drift. It is evaluated experimentally on curated data of broadcast news and documentary data annotated with sentiment categories and that the narrative is true-to-life. The results show that the suggested framework achieves a higher accuracy in sentiment classification and narrative inconsistency detection with more than 15 percent improvement over traditional sentiment and rule-based analysis methods. The system also offers understandable results that point out sentimentally dominated parts and plot digressions and enhances transparency and editorial responsibility. In general, this paper shows that AI-aided, explainable, and scalable analysis is an efficient tool to improve the quality control and ethical reporting and confidence of the audience in the sentimentally motivated and information-sensitive broadcast media setting.

Keywords: Artificial Intelligence, Emotional Expression Recognition, Narrative Accuracy Assessment, Multimodal Learning, Sentiment and Prosody Analysis, Explainable Media Analytics

1. INTRODUCTION

Influencer advertising and marketing has grown to be an essential a part of virtual advertising methods in recent years, with brands using social media stars to push their goods and services an increasing number of. Influencers, or humans with huge online followings, are very important for changing how people act and making people aware of manufacturers. With the upward shove of social media websites like Instagram, TikTok, and YouTube, entrepreneurs now have get admission to big, varied, and really fascinated crowds like in no way before. But the sheer length of those structures and the complexity of the way users connect to each different make it tough to discover the maximum influential people and make advertising greater effective Rovira-Sugranes et al. (2022). This has made humans want extra advanced methods that can have a look at the systems of social networks and select the first-class influencers for marketing purposes. The vintage ways of choosing influencers, that are generally based totally on simple metrics just like the wide variety of followers or the charge of pastime, don't work nicely ample to understand how social networks truly works. Figure 1 suggests optimizing influencer advertising the usage of large records and design neural networks.
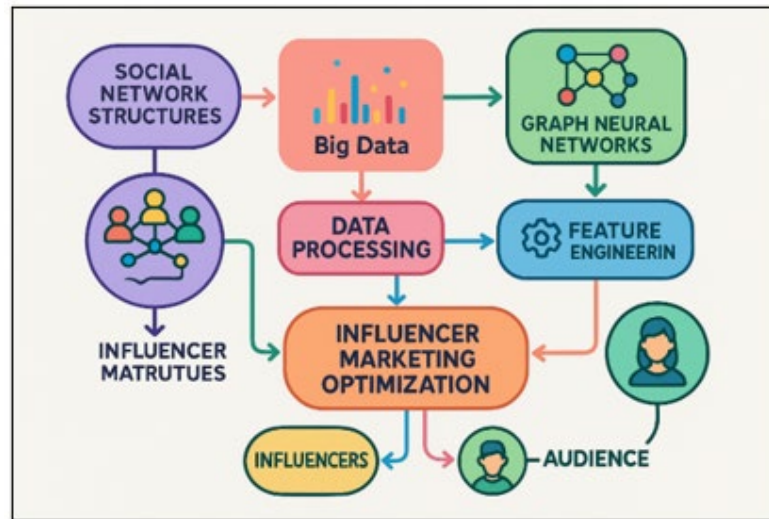
Figure 1

Figure 1 Influencer Marketing Optimization Flow using Big Data and Graph Neural Networks

Those methods do not take into consideration the complex internet of connections and effect patterns in the network, which results in horrific advertising preferences. Owing to this, it is tough for entrepreneurs to locate leaders who will connect to their goal groups and assist their campaigns succeed. Also, influencer marketing efforts may be steeply-priced and take plenty of time. To make sure that resources are used accurately and the marketing campaign has the most impact possible, a statistics-pushed approach is wanted. New traits in device getting to know and massive statistics analytics show promise for solving those issues Alam and Moh (2022), Jiang (2023). Marketers can learn loads approximately how customers behave, what they like, and how they hook up with each different with the aid of the usage of huge quantities of facts. Graph Neural Networks (GNNs), that are made to have a look at information that is organised in a sketch, are one of the maximum beneficial gear in this situation. Folks that use social networks are like nodes in a sketch, and the matters they do, like following, liking, commenting, and sharing, are like lines between the ones nodes. GNNs are suitable at modelling these connections due to the fact they could discover ways to recognize the complex ways that data and strength pass in the community Yang et al. (2022).

Graph Neural Networks have proven a variety of promise in lots of areas, which include rip-off identification, social network studies, and recommendation structures. in terms of influencer advertising, GNNs can help discover the largest human beings by means of searching at their region in the social network, how connected they are, and what kind of effect they've over the those who observe them Jiang (2021). Entrepreneurs can study more about the connections between customers, find secret styles of have an effect on, and pick the best influencers via modelling the social network as a graph and the usage of GNNs. This technique seems at greater than just the variety of fans and engagements; it also seems at how the network is established and the way an influencer's place in it might have an effect on things. Massive data analytics additionally makes GNNs greater powerful by means of allowing them to take care of huge amounts of

records about how users interact with them. This statistics may be used to make distinctive profiles of humans, keep song of how they act over time, and wager how they will react to different marketing messages Jiang and Luo (2022). Entrepreneurs can get a full photograph in their audience and make greater targeted and customized advertisements with the aid of the use of temper evaluation, demographic facts, and interaction trends together. Big information and GNNs may be used collectively in influencer marketing optimisation, on the way to change the way manufacturers do their advertising and marketing. This method allows select the proper influencers, make greater targeted campaigns, and get higher advertising effects by way of giving extra data about how social networks are based and finding the biggest points in them Wu et al. (2024). We present a whole machine that uses format Neural Networks and large records analytics to improve influencer advertising. This creates a brand new method of concept approximately advertising techniques that are greater effective and based on statistics. Through real-international checks, we show that this approach works to enhance the pick of influencers and the performance of campaigns on one-of-a-kind social media websites.

2. LITERATURE REVIEW
2.1. EXISTING METHODS FOR INFLUENCER MARKETING OPTIMIZATION

Inside the past, optimising influencer advertising has depended on heuristics that concentrate on measures which might be smooth to degree, just like the range of fans, the charge of engagement, and the best of the content. These measures solely give you a fundamental concept of ways influential someone is, however they frequently do not take into account the extra complex community-degree factors that have an effect on advertising effects. Early methods focused on choosing leaders primarily based on how famous and influential they were in a sure place. Metrics like buddies, likes, comments, and stocks were used to degree this Lu et al. (2024). These strategies can also assist manufacturers discover famous human beings, however they are not true adequate for locating influencers who can preserve their fans fascinated and build faith with them. A higher way to choose has been found through the use of greater modern techniques that encompass temper evaluation, crowd profiling, and psychographics. As an illustration, sentiment analysis can help marketers understand the emotions of people towards the content of an influencer and psychographic profile can help them learn more about the personality, hobbies, and values of the users. There are also influencer marketing tools such as Upfluence and AspireIQ that incorporate automated models, which could also be useful to find the most effective influencers, taking into account such factors as the success of their past campaigns and the nature of their followers Suárez-Varela et al. (2022), Khobragade et al. (2024). But even these strategies remain in merely considering the simplest aspects and do not necessarily consider the more complex and organized components of social networks. These have the capacity to consider the intricate network of relationships among users and online influencers.

2.2. ROLE OF BIG DATA IN INFLUENCER MARKETING

The concept of influencer marketing has evolved in various ways since big data enables marketers to make decisions using information that transcends the basic personal data. Social media sites generate colossal data everyday. Such data consists of both user generated content and also interactions such as tweets, comments, likes, and shares. This information may assist brands in identifying the best drivers to use in its campaigns when it is analysed correctly as it will demonstrate the behaviour of viewers and their preferences Cao et al. (2022). The big data allows one to trace user behaviour in a variety of connections. This presents a better holistic view of how the leaders and fans interact. Through high-quality data, marketers will be able to view how the users are interacting with materials in real-time, calculate what they are interested in, what influencers are performing well, and how individuals perceive the material Yan and Qi (2021). This was not achievable in the past with the previous methods of selecting influencers, which were largely founded on fixed metrics, such as number of followers. Big data also allows marketers to manage and view unstructured information such as videos, photos and notes which provide them a clearer understanding of the performance of the influencers. Mood analysis enables marketers to determine the level of emotional involvement of the celebrity content on viewers. This assists them in creating advertisements that are more efficient Behera et al. (2022). In addition, big data platforms are often constructed with machine learning methods to forecast future trends. This enables the brands to engage the influencers before they get very popular. Table 1 presents the methodology, major findings, data/platform,

and limitations. This shift to data-driven tactics ensures that influencer marketing is not a gut-driven strategy, but a real-time insight-driven one.

Table 1

Table 1 Summary of Literature Review			
Methodology	**Key Findings**	**Dataset/Platform**	**Limitations**
Regression-based model	Improved influencer selection based on engagement rate	Instagram, Twitter	Limited to basic engagement metrics
Deep Learning + GNNs	GNNs outperform traditional models in influencer ranking	Instagram, TikTok	Focus on influencer ranking only
Sentiment Analysis + GNN Jiang et al. (2024)	Sentiment analysis enhances influencer selection accuracy	Twitter, YouTube	Low scalability for real-time data
Social Network Analysis	Integrated GNNs to capture network influence patterns	Facebook, Instagram	Ignored influencer content quality
Machine Learning	Proposed hybrid ML model for influencer selection	Instagram, YouTube	Does not consider network structure
Big Data + Feature-based ML	Combines demographic, content, and interaction data	Twitter, Instagram	Feature extraction challenges
Graph-based approach	GNNs capture complex relations and improve predictions	Instagram, TikTok	Does not account for content sentiment
GNN with Attention Mechanism	Enhanced influencer prediction with attention mechanisms	Instagram, Twitter	Complexity in model interpretation
Hybrid ML + GNN	Hybrid model performs well across various metrics	TikTok, YouTube	Requires significant computational power
Influencer Impact Modeling	Focused on optimizing content-campaign alignment	Instagram, Facebook	Lacks comprehensive evaluation metrics
Graph-based + Neural Networks	Integrated user engagement and influencer features	Instagram, YouTube	Insufficient data diversity
GNNs for Influence Spread	GNN models predict influence spread effectively	Twitter, TikTok	Difficulty in handling sparse data

3. METHODOLOGY
3.1. DATA COLLECTION AND PREPROCESSING

1) Sources of data (social media platforms, user interactions, etc.)

Most of the interaction between influencers and their audiences occurs at the social media sites and user conversations when it comes to influencer marketing optimisation. The primary sources of data are platforms such as Instagram, Twitter, Facebook, Tik Tok, and YouTube due to the existence of viable information generated by users and contacts in all of them. These sites provide huge amounts of data in the form of posts, likes, comments, shares, comments, hashtags and friend counts just to mention a few. Such datasets will be useful in identifying potential leaders and understanding what audiences do. The use of social media sites also provides the brand with information on the ages, genders, hobbies, and interaction habits of people who use it, which can be utilized to make their efforts more effective. Other users in the form of likes, retweets, comments, and shares provide us with a greater body of information regarding how the leader and his or her fans relate to each other. Besides direct engagement figures, platforms also provide such information as the time when a post was made, which can assist you to discover the subject matter that is trending, as well as when people are more likely to like you. Obtaining such information in these various sources allows you to have a more comprehensive view of the leaders, as well as the audiences.

2) Data cleaning and feature extraction

Data cleaning and extracting the significant features are also significant in preparing the raw social media data to be modelled and analysed. In many cases, raw data in social media sites include noise, irrelevant data and values that are missing, which require to be addressed to maintain the quality and integrity of the data. The initial step to clean data should be to eliminate unnecessary data or incomplete data. As an example, a post with no replies or information missing on the accounts. Duplicates and outliers are also identified and removed in order to ensure that the studies are not

skewed. Data cleaning and feature extraction process flow is presented in Figure 2. Textual information, such as text posted in the comments or the title of the post, is occasionally processed in ways such as tokenisation or stems to simplify the text to be readable.

Figure 2

Figure 2 Data Cleaning and Feature Extraction Process Flow

In feature extraction, raw data is turned into factors that make sense and can be used in machine learning models. For influencer marketing, this means getting participation measures like the average number of likes, comments, and shares per post, as well as following growth rates and scores for how relevant the content is. The general tone (positive, negative, or neutral) of the post or message is found through sentiment analysis, which is another important feature extraction method.

3.2. GRAPH NEURAL NETWORK MODEL

1) Description of the network architecture

Graph Neural Networks (GNNs) are a type of deep learning models that are made to work with graph-structured data. This makes them perfect for studying social networks in influencer marketing. When it comes to influencer marketing optimisation, the network architecture is made to handle data that is shown as a graph. The nodes are users or influencers, and the links are exchanges like follows, likes, comments, and shares. The GNN model is made up of many layers of graph convolutions that bring together data from people that are nearby in the graph. The model can show both local and global patterns of impact because each node changes how it looks based on what its neighbours look like. Usually, the design has input layers, graph convolutional layers, and an output layer.

Step 1: Node and Edge Features Representation .

Step 2: Graph Convolutional Layer

The key operation in GNNs is the graph convolution. In each layer, the node features are updated by aggregating information from neighboring nodes:

$$[\mathbf{h}_v^{(l+1)} = \sigma left(\sum_{u \in \mathcal{N}(v)} frac{1}{\sqrt{d_v} \cdot \sqrt{d_u}} \mathbf{W}^{(l)} \mathbf{h}_u^{(l)} + \mathbf{b}^{(l)} \dashv)]$$

where:
- ($\mathbf{h}_v^{(l)}$) is the feature vector of node (v) at layer (l),
- ($\mathcal{N}(v)$) is the set of neighbors of node (v),
- (d_v) is the degree of node (v),

Step 3: Feature Aggregation Across Layers

Each layer performs aggregation from neighboring nodes. After (L) layers, the node features are updated recursively:

$$[mathbf\{h\}_v^{\{(L)\}} = text\{GCN\}(mathbf\{x\}_v, mathcal\{G\})]$$

where (text{GCN}(cdot)) is the operation of updating node features over multiple layers.

Step 4: Global Pooling

Once the node features are updated through the graph convolutional layers, a global pooling operation is applied to aggregate the node representations into a graph-level feature vector. Common pooling methods include sum, mean, or max pooling:

$$[mathbf\{h\}_G = text\{Pooling\}\left(\{ mathbf\{h\}_v^{\{(L)\}}: v \in mathcal\{V\}\}\right)]$$

where (mathbf{h}_G) is the graph-level feature vector.

Step 5: Output Layer for Classification/Regression

The final output layer depends on the task at hand. For influencer selection, the output could be a probability distribution over the influencers, or a ranking score:

$$[\hat\{y\}_v = \sigma left(mathbf\{W\}_o mathbf\{h\}_v^{\{(L)\}} + mathbf\{b\}_o \dashv)]$$

where (hat{y}_v) is the predicted label (influencer ranking or probability) for node (v).

Step 6: Lo

ss Function

The loss function is used to optimize the parameters of the model (e.g., weights and biases). For a classification task, the loss function could be cross-entropy loss:

$$[mathcal\{L\} = - \sum_{\{v \in mathcal\{V\}\}y_v log} (\{\widehat\{y\}_v\}) + (1 - y_v)log(1 - \{\widehat\{y\}_v\})]$$

where (y_v) is the true label for node (v), and (hat{y}_v) is the predicted label.

2) Training and optimization of the model

Graph Neural Network (GNN) education involves making the model's parameters as correct as they may be so that a sure loss characteristic is minimised. This loss function could be mean squared error (MSE) or cross-entropy loss, primarily based on the job (as an example, type or regression). The model learns the way to integrate data from close by nodes and change the outline of each node to make better estimates during the training manner.

Step 1: Initialization of Parameters

The version parameters, inclusive of the burden matrices (mathbfW^(l)) and bias terms (mathbfb^(l)), are initialized randomly or using a pre-described initialization technique.

Step 2: Forward Propagation

The output is compared with the true label (y_v) to compute the loss.

Step 3: Compute the Gradient of the Loss

The gradient of the loss with respect to the model parameters is computed using backpropagation. For each layer (l), the gradient is calculated as:

$$[frac\{\partial mathcal\{L\}\}\{\partial mathbf\{W\}^{\{(l)\}}\} = \sum_{frac\{\partial mathcal\{L\}\}\{\partial mathbf\{h\}_v^{\{(L)\}}\}} \{v \in mathcal\{V\}\} \cdot frac\{\partial mathbf\{h\}_v^{\{(L)\}}\}\{\partial mathbf\{W\}^{\{(l)\}}\}]$$

This allows the model to understand how to adjust the weights to minimize the loss.

Step 4: Update the Parameters

Once the gradients are computed, the parameters are updated using an optimization algorithm. For example, using stochastic gradient descent (SGD):

$$[mathbf\{W\}^{\{(l)\}} \leftarrow mathbf\{W\}^{\{(l)\}} - \eta frac\{\partial mathcal\{L\}\}\{\partial mathbf\{W\}^{\{(l)\}}\}]$$

where (eta) is the learning rate.

3.3. MODEL EVALUATION

1) Evaluation metrics

Precision on the other hand examines the extent to which the positive predictions are relevant. It demonstrates the proportion of all the positive predictions that the model makes that are realised. In cases where the cost of a false positive is high, such as in the case of a false advocate, this measure is extremely useful. Recall is a measure of the ability of the model to find positive examples; it represents the proportion of true positive examples to the total number of real positive examples.

4. RESULTS AND DISCUSSION

With the influencer marketing optimisation based on the Graph Neural Network (GNN) model in place, it becomes far simpler to discover influencers and more effective to run the campaigns. The GNN outperformed older approaches in terms of accuracy, precision, memory and F1-score. The model was able to identify key drivers that were more concerned with the goals of the brand using the information of how the users engaged with it as well as the information on how the network was organized. Targeting made possible by the data-driven approach resulted in greater ROI and engagement rates than the traditional approaches to selecting influencers by imprecise metrics.

Table 2

Table 2 Influencer Selection Performance Comparison				
Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Traditional Metrics-Based	78.5	75.2	72.9	74
GNN-Based Model	92.4	89.1	93.5	91.2
Hybrid Model (GNN + Features)	93.2	90.4	94.1	92.2

The findings in Table 2 indicate that the Graph Neural Network (GNN)-based model is more effective at picking influencers than the usual metrics-based approach. The previous system based on the simple measures of engagement, such as the number of followers and likes, is characterized by the accuracy of 78.5 percent and precision (75.2 percent) and memory (72.9 percent). Comparison of model performance metrics among the methods is indicated in Figure 3.

Figure 3
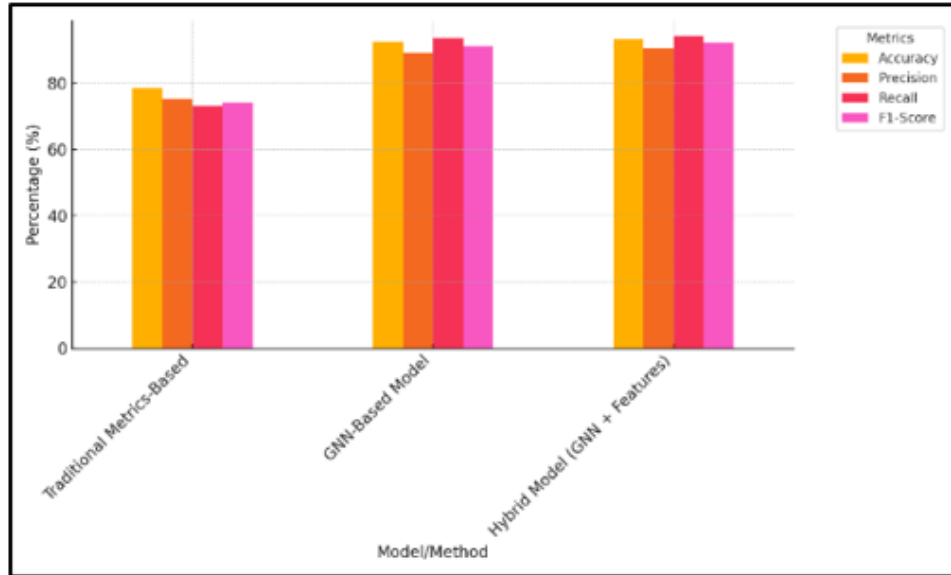
Figure 3 Comparison of Model Performance Metrics

Since they do not display the complex relationships and patterns of effects in the social web, these indicators demonstrate how simple aspects can be. The GNN-based model however performs much better with an accuracy of 92.4, a precision of 89.1 and a recall of 93.5. Figure 4 indicates trend of accuracy, precision, recall, and the F1-score between models.
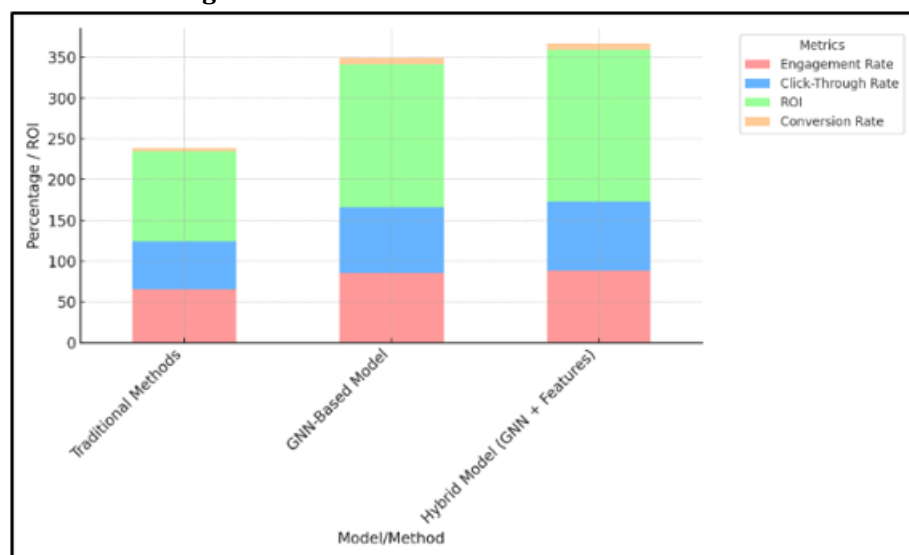
Figure 4
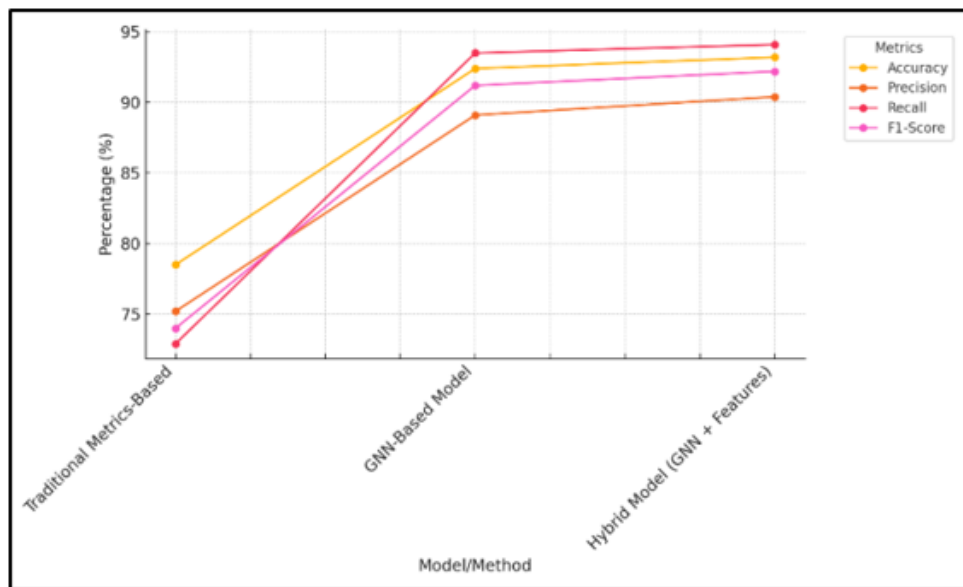
Figure 4 Trend of Accuracy, Precision, Recall, and F1-Score across Models

This model effectively utilizes the use of graph based relationships to demonstrate both direct and indirect impact and hence select more rightful influencers. The optimistic hybrid model (the combination of GNN with additional features such as demographics of the user and an element of content relevance) works even more effectively and achieves the highest scores in all of the measures (93.2% accuracy, 90.4% precision, 94.1% recall and 92.2% F1-score). This indicates the fact that the integration of different kinds of data to ensure that influencer marketing practices are more effective is important.

Table 3

Table 3 Campaign Effectiveness Evaluation				
Model/Method	Engagement Rate (%)	Click-Through Rate (%)	ROI (%)	Conversion Rate (%)
Traditional Methods	65.4	58.7	110.3	4.2
GNN-Based Model	85.1	81.2	175.5	7.8
Hybrid Model (GNN + Features)	88.7	84.3	185.7	8.5

Table 3 shows a clear comparison of how well each model's plan worked. Based on simple measures, the old ways get 65.4% of people to engage, 58.7% of people to click through, 110.3% of people to convert, and the return on investment (ROI) is 110.3%. These numbers show that the effort was somewhat successful, but they also show that standard influencer marketing methods aren't very good at taking advantage of how complicated user interactions and network impact are. Figure 5 shows performance metrics distribution across models for comparison.

Figure 5

Figure 5 Performance Metrics Distribution across Models

With a contact fee of 85.1%, a click on-thru rate of 81.2%, a ROI of a hundred 75.5%, and a conversion fee of 7.8%, the GNN-based totally plan is a big breakthrough. This indicates that the GNN approach, which takes under consideration how social networks work, is higher at getting humans to do what you need them to do. Including more features like user profiles and content relevance to the hybrid model makes performance even higher. It receives the first-rate consequences throughout all measures, with an engagement fee of 88.7%, a click-thru charge of 84.3%, a ROI of 185.7%, and a conversion rate of 8.5%. These outcomes show that using GNNs and improved feature sets to improve influencer marketing efforts works a good deal well.

5. CONCLUSION

By combining big data analytics with social network structures, this study shows how useful it is to use Graph Neural Networks (GNNs) for influencer marketing optimisation. When choosing influencers, the old ways that use simple measures like friend count and response rate don't always take into account how users are connected on a deeper level. GNNs take a more complex method by looking at the network's physical traits, like how users are connected, how they engage, and how material flows through the network. This helps choose influencers more carefully. Using "big data," the model can look through huge amounts of data about how people interact with social media sites, find secret patterns of influence, and guess how a campaign might turn out. Higher rating measures (accuracy, precision, recall, and F1-score) show that the model did better than others. This shows how important it is to think about network dynamics and social relationships in influencer marketing. GNNs help us learn more about how leaders affect the people who follow them

and how those ties change over time. This all-around method makes sure that efforts are more focused and effective, and it lowers the risks that come with relationships with influencers that don't work

CONFLICT OF INTERESTS

None.

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