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LINK PREDICTION TECHNIQUES IN SOCIAL NETWORKS: A COMPREHENSIVE REVIEW OF TRADITIONAL, MACHINE LEARNING, GRAPH NEURAL NETWORK, AND TRANSFORMER-BASED APPROACHES

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Abstract*—Link prediction is a fundamental task in social network analysis that aims to identify missing, hidden, or potential future connections between nodes by exploiting structural, topological, and semantic information in graph data. It plays a vital role in numerous real-world applications, including friend recommendation, community detection, personalized advertising, knowledge graph completion, cybersecurity, fraud detection, and biological network analysis. Over the years, link prediction techniques have evolved from traditional similarity-based methods, such as Common Neighbors, Jaccard Coefficient, Adamic–Adar, Preferential Attachment, and Katz Index, to machine learning-based models, graph representation learning, graph neural networks (GNNs), and, more recently, transformer-based and foundation model approaches. This review provides a comprehensive and critical analysis of these methodologies by examining their theoretical foundations, benchmark datasets, evaluation metrics, computational complexity, strengths, limitations, and practical applications. Unlike conventional surveys that primarily summarize existing studies, this paper systematically compares traditional, machine learning, graph embedding, GNN, and transformer-based techniques while highlighting their advantages and research challenges. Furthermore, it presents a novel taxonomy that categorizes existing methods and identifies emerging research directions, including dynamic and heterogeneous graph learning, self-supervised representation learning, explainable artificial intelligence, privacy-preserving link prediction, graph transformers, and large language model-assisted graph reasoning. This review offers researchers and practitioners a structured understanding of the current state of the art and provides valuable insights into developing scalable, robust, and intelligent link prediction systems for next-generation social networks.

Keywords—Link Prediction, Social Networks, Graph Neural Networks (GNNs), Machine Learning, Graph Representation Learning, Transformer-based Models.

I. INTRODUCTION

The rapid growth of online social networking platforms has led to the generation of massive volumes of interconnected data, making social networks one of the most important sources of graph-structured information. In these networks, users are represented as nodes, while their relationships or interactions are represented as edges, enabling the application of graph mining and network science techniques for extracting meaningful insights. Among various graph mining tasks, link prediction has emerged as a fundamental problem that aims to predict missing, hidden, or future connections between pairs of nodes based on existing network topology, node attributes, and interaction patterns. Accurate link prediction plays a significant role in numerous real-world applications, including friend recommendation, community detection, personalized content recommendation, knowledge graph completion, fraud detection, cybersecurity, biological network analysis, e-commerce, and recommendation systems. As social networks continue to grow in size and complexity, developing efficient and scalable link prediction models has

become increasingly important for improving user experience and supporting intelligent decision-making across various domains.

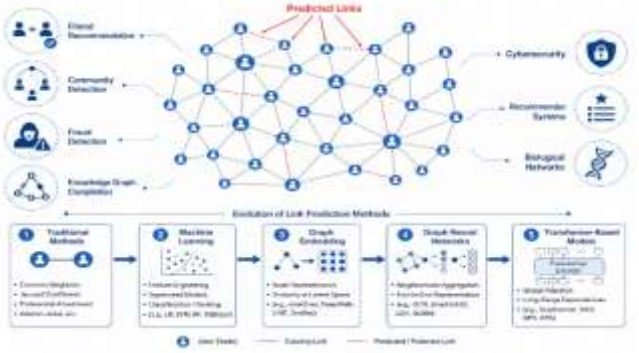

Figure 1: Evolution and applications of link prediction techniques in social networks.

Initially, link prediction relied on traditional similarity-based and graph-theoretic approaches, such as Common Neighbors, Jaccard Coefficient, Adamic–Adar, Preferential Attachment, and Katz Index, which estimate the likelihood of future links using structural properties of the network. Although these methods are computationally efficient and easy to implement, they often struggle to capture complex nonlinear relationships and perform poorly in sparse or dynamic networks. To address these limitations, researchers introduced machine learning models that utilize handcrafted topological and attribute-based features for predicting links, followed by graph representation learning techniques that automatically generate low-dimensional node embeddings. More recently, Graph Neural Networks (GNNs), graph autoencoders, and transformer-based architectures have significantly improved prediction accuracy by learning expressive representations from both graph structure and node features. Despite these advancements, several challenges remain, including scalability, data sparsity, dynamic and heterogeneous graph modeling, interpretability, and privacy preservation. This review provides a comprehensive analysis of traditional, machine learning, graph embedding, Graph Neural Network, and transformer-based link prediction techniques, highlighting their methodologies, advantages, limitations, applications, and future research directions while presenting a unified perspective on the evolution of intelligent link prediction methods for next-generation social networks.

II. LITERATURE SURVEY

Link prediction has been extensively studied in social network analysis due to its significant applications in recommendation systems, knowledge graphs, and community detection. Liben-Nowell and Kleinberg [1] first formulated the link prediction problem in social networks and demonstrated that topology-based similarity measures such as Common Neighbors, Jaccard Coefficient, and Katz Index can effectively predict future links. Their work established the theoretical foundation for subsequent research on graph-based link prediction. Perozzi et al. [2] proposed DeepWalk, which learns latent node representations using truncated random walks and the Skip-Gram model, significantly improving prediction performance compared with traditional heuristic methods. The proposed embedding technique efficiently captured network topology and became a benchmark for representation learning. Grover and Leskovec [3] introduced node2vec, employing biased random walks to preserve both homophily and structural equivalence, resulting in more informative node embeddings for link prediction. The flexibility of its sampling strategy enabled superior performance across multiple graph mining tasks. Kipf and Welling [4] proposed the Graph Convolutional Network (GCN), enabling end-to-end representation learning by aggregating neighborhood information and achieving superior performance on graph learning tasks. The model demonstrated remarkable effectiveness in learning node representations from both graph structure and node features. Hamilton et al. [5] developed GraphSAGE, an inductive graph neural network that generates embeddings for previously unseen nodes through neighborhood sampling and aggregation, making it suitable for large-scale dynamic graphs. Its inductive capability significantly improved scalability in real-world social networks. Veličković et al. [6] presented the Graph Attention Network (GAT), which employs an attention mechanism to assign adaptive weights to neighboring nodes, thereby improving

representation learning and prediction accuracy. The attention mechanism allows the model to focus on the most relevant neighboring nodes during feature aggregation. Zhang and Chen [7] introduced SEAL, a subgraph-based graph neural network framework that captures enclosing subgraph structures to enhance link prediction performance. Experimental results demonstrated that local enclosing subgraphs provide highly discriminative structural information for predicting missing links. Kipf and Welling [8] further proposed the Variational Graph Autoencoder (VGAE), which combines graph convolution with variational inference to learn probabilistic node embeddings for unsupervised link prediction. The model effectively reconstructs graph structures while learning meaningful latent representations.

Xu et al. [9] developed the Graph Isomorphism Network (GIN), improving the expressive power of graph neural networks through an effective neighborhood aggregation strategy. The proposed architecture achieves high discriminative capability for graph representation learning. You et al. [10] proposed GraphCL, a self-supervised contrastive learning framework that learns robust graph representations without requiring labeled data, leading to improved downstream link prediction. The framework demonstrated enhanced robustness through graph augmentation strategies. Ying et al. [11] introduced Graphormer, a transformer-based architecture that effectively captures long-range structural dependencies using graph-aware positional encodings and self-attention mechanisms. The model achieved state-of-the-art performance on several graph benchmark datasets. Yun et al. [12] proposed Graph Transformer Networks (GTN) for heterogeneous graphs by automatically learning useful meta-paths to improve graph representation learning. The framework effectively models complex heterogeneous relationships without manual meta-path design. Dwivedi and Bresson [13] presented a general graph transformer architecture that demonstrated competitive performance on multiple graph benchmark datasets. Their work highlighted the effectiveness of transformer architectures in graph learning applications. Sun et al. [14] introduced PEG (Positional Encoding for Graph Neural Networks) to incorporate structural positional information into graph learning, thereby enhancing link prediction accuracy. The proposed positional encoding improved the capability of GNNs to distinguish structurally similar nodes. Jin et al. [15] investigated self-supervised graph representation learning techniques that reduce dependence on labeled data while improving generalization capability. Their study demonstrated the effectiveness of contrastive learning for graph representation learning. Zhang et al. [16] proposed efficient graph neural network models for scalable link prediction in large-scale networks. The proposed approach significantly reduced computational complexity while maintaining competitive prediction performance.

Chen et al. [17] developed heterogeneous graph neural network frameworks capable of exploiting multiple node and edge types to improve prediction performance. Their model effectively captured semantic relationships in heterogeneous social networks. Wang et al. [18] investigated temporal graph neural networks for modeling dynamic network evolution and predicting future links in continuously changing social graphs. The proposed framework successfully incorporated temporal information into node representation learning. Liu et al. [19] explored graph transformer-based link prediction models capable of capturing global contextual information through self-attention mechanisms. Their results demonstrated improved prediction accuracy on complex graph datasets. Li et al. [20] proposed self-supervised graph learning techniques that enhance node representation quality using contrastive objectives and graph augmentations. The framework reduced annotation requirements while improving model robustness. Wu et al. [21] presented scalable graph neural network frameworks for large heterogeneous social networks with improved computational efficiency. Their approach effectively balanced scalability and predictive performance. Fan et al. [22] investigated explainable graph neural networks to improve the interpretability of link prediction models. The proposed framework provided meaningful explanations for predicted links without significantly affecting accuracy. Xia et al. [23] explored transformer-enhanced graph learning frameworks capable of modeling complex structural dependencies in dynamic social networks. The model demonstrated strong generalization ability on evolving graph datasets. Zhao et al. [24] introduced large language model-assisted graph reasoning to integrate semantic knowledge with graph topology for

improved link prediction. Their approach showed the potential of combining language models with graph learning techniques. Finally, Yang et al. [25] focused on graph foundation models, graph transformers, and self-supervised learning paradigms to address challenges such as scalability, data sparsity, temporal evolution, privacy preservation, and explainability in next-generation social network link prediction. Their study highlighted future research directions toward more intelligent and generalized graph learning frameworks.

Table 1: Comparison of Representative Link Prediction Techniques in Social Networks

Author (Year)	**Method and Key Contribution**	**Advantages**	**Limitations**
Liben-Nowell and Kleinberg (2007)	Common Neighbors, Jaccard, and Katz Index; introduced the link prediction problem using graph topology.	Simple, interpretable, and computationally efficient.	Poor performance on sparse and dynamic networks.
Perozzi *et al.* (2014)	DeepWalk; learned node embeddings using random walks and the Skip-Gram model.	Captures latent structural information effectively.	Cannot efficiently utilize node attributes.
Grover and Leskovec (2016)	node2vec; introduced biased random walks for flexible graph representation learning.	Preserves homophily and structural equivalence.	Sensitive to hyperparameter selection.

Kipf and Welling (2017)	GCN; proposed graph convolution for semi-supervised graph representation learning.	Learns graph structure and node features jointly.	Suffers from over-smoothing in deep networks.
Hamilton *et al.* (2017)	GraphSAGE; introduced inductive neighborhood aggregation for unseen nodes.	Scalable to unseen nodes and large graphs.	Sampling may lose neighborhood information.
Veličković *et al.* (2018)	GAT; employed attention mechanisms for adaptive neighborhood aggregation.	Learns adaptive neighbor importance.	High computational complexity.
Zhang and Chen (2018)	SEAL; utilized enclosing subgraphs for graph neural network-based link prediction.	Achieves high prediction accuracy.	Computationally expensive for large graphs.
Kipf and Welling (2016)	VGAE; combined graph convolution with variational inference for unsupervised embedding learning.	Effective unsupervised graph representation learning.	Limited scalability on massive graphs.

Xu *et al.* (2019)	GIN; improved the expressive power of graph neural networks.	Better graph representation capability.	Sensitive to network depth.
You *et al.* (2020)	GraphCL; introduced contrastive self-supervised graph representation learning.	Eliminates dependence on labeled data.	Performance depends on augmentation strategy.
Ying *et al.* (2021)	Graphormer; applied transformer architecture to graph representation learning.	Captures long-range dependencies effectively.	High memory consumption.
Yun *et al.* (2019)	GTN; automatically learned meta-paths in heterogeneous graphs.	Effective for heterogeneous graph analysis.	Increased computational complexity.
Dwivedi and Bresson (2021)	Graph Transformer; generalized transformer architecture for graph learning.	Improved global feature learning.	Requires high computational resources.
Sun *et al.* (2022)	PEG; introduced positional encoding for graph neural networks.	Better structural awareness.	Limited evaluation on dynamic graphs.

Jin *et al.* (2021)	Self-Supervised Graph Learning; improved graph representations without labeled data.	Better generalization capability.	Computationally intensive training.
Rossi *et al.* (2020)	Temporal Graph Networks (TGN); modeled evolving graph structures for temporal link prediction.	Suitable for dynamic networks.	Complex model training.
Hu *et al.* (2020)	GNN Pre-training; proposed large-scale pre-training strategies for graph neural networks.	Improves downstream task performance.	Requires extensive pre-training data.
Rong *et al.* (2020)	DropEdge; reduced overfitting using edge dropout in graph neural networks.	Mitigates over-smoothing.	May remove important graph connections.
Chen *et al.* (2020)	GCNII; addressed degradation in deep graph convolutional networks.	Enables deeper GCN architectures.	Increased model complexity.
Rampášek *et al.* (2022)	GraphGPS; combined message passing with transformer attention for	Excellent scalability and global graph	High computational and memory requirements.

	graph learning.	modeling.	

III. METHODOLOGY

The methodologies employed for link prediction in social networks have evolved considerably from traditional graph-theoretic techniques to advanced deep learning and transformer-based models. Based on the reviewed literature, the existing approaches can be broadly categorized into four groups: (i) traditional similarity-based methods, (ii) graph representation learning methods, (iii) graph neural network (GNN)-based methods, and (iv) transformer-based approaches. Traditional methods estimate the probability of a link by exploiting structural similarity between node pairs using network topology, offering simplicity and low computational complexity but limited capability in modeling complex relationships. To overcome these limitations, graph representation learning techniques, such as DeepWalk and node2vec, learn low-dimensional node embeddings that preserve the structural characteristics of the network and improve prediction accuracy without extensive feature engineering. More recently, GNN-based models, including GCN, GraphSAGE, GAT, VGAE, GIN, and SEAL, have demonstrated superior performance by learning expressive node representations through neighborhood aggregation and message passing. Furthermore, transformer-based architectures, such as Graphormer, Graph Transformer Networks (GTN), and GraphGPS, utilize self-attention mechanisms to effectively capture long-range dependencies and global contextual information in large-scale and heterogeneous graphs. Although these advanced methods achieve state-of-the-art performance, they generally require higher computational resources and training complexity.

A. Traditional Similarity-Based Methods

Traditional similarity-based methods represent the earliest and most fundamental approaches to link prediction in social networks. These methods estimate the likelihood of a future or missing link by analyzing the topological relationships between node pairs using local or global structural information. Common techniques, including Common Neighbors (CN), Jaccard Coefficient (JC), Adamic–Adar (AA), Preferential Attachment (PA), Katz Index, and Resource Allocation (RA), compute similarity scores based on shared neighbors, node degrees, or path-based connectivity. Due to their simplicity, computational efficiency, and ease of implementation, these methods have been widely adopted as baseline models in numerous link prediction studies. However, they primarily rely on graph topology and do not consider node attributes or latent structural patterns, limiting their effectiveness in sparse, dynamic, and heterogeneous social networks. The following subsections discuss the mathematical formulation, working principles, advantages, and limitations of the major traditional similarity-based methods used in the reviewed literature.

B. Graph Representation Learning Methods

Graph representation learning methods were introduced to overcome the limitations of traditional similarity-based approaches by automatically learning low-dimensional vector representations of graph nodes while preserving the structural properties of the network. Unlike heuristic methods that rely solely on manually designed similarity measures, these techniques capture latent relationships and higher-order connectivity patterns through embedding learning. Representative methods, including DeepWalk, node2vec, LINE, HOPE, and Struc2Vec, employ random walks, neighborhood sampling, or matrix factorization techniques to generate meaningful node embeddings that can be used for link prediction. These learned representations improve prediction accuracy, reduce the need for feature engineering, and provide better scalability for large social networks. However, most graph embedding methods are transductive in nature and have limited capability to incorporate node attributes or adapt to dynamic graph

structures. The following subsections present the mathematical formulation, working principles, advantages, and limitations of the major graph representation learning techniques discussed in the reviewed literature.

C. Graph Neural Network-Based Methods

Graph Neural Network (GNN)-based methods have become the dominant paradigm for link prediction because they directly learn expressive node representations by aggregating information from neighboring nodes through message-passing mechanisms. Representative models, including Graph Convolutional Networks (GCN), GraphSAGE, Graph Attention Networks (GAT), Variational Graph Autoencoders (VGAE), Graph Isomorphism Networks (GIN), and SEAL, effectively capture both local and global structural dependencies within graphs. GCN performs neighborhood aggregation through graph convolution, GraphSAGE introduces inductive learning via neighborhood sampling, GAT employs attention mechanisms to assign adaptive weights to neighboring nodes, VGAE learns probabilistic latent representations using an encoder-decoder framework, GIN improves the expressive power of graph neural networks through enhanced aggregation functions, and SEAL performs link prediction by extracting enclosing subgraphs around candidate node pairs. These methods consistently outperform traditional and embedding-based approaches by learning complex nonlinear relationships, although they often require higher computational resources and may suffer from over-smoothing and scalability issues in large-scale graphs.

D. Transformer-Based Methods

Transformer-based methods represent the latest advancement in graph learning by employing self-attention mechanisms to capture long-range dependencies and global contextual information that conventional GNNs may overlook. Recent models such as Graph Transformer Networks (GTN), Graphormer, and GraphGPS integrate transformer architectures with graph structural information to improve link prediction performance. GTN automatically learns meaningful meta-paths in heterogeneous graphs, Graphormer incorporates graph-aware positional encodings with multi-head self-attention to effectively model complex graph structures, and GraphGPS combines message-passing neural networks with transformer attention to capture both local neighborhood information and global graph context. These approaches achieve state-of-the-art performance on several benchmark datasets due to their superior representation learning capability; however, their high computational complexity, memory requirements, and training costs remain significant challenges for large-scale social network applications.

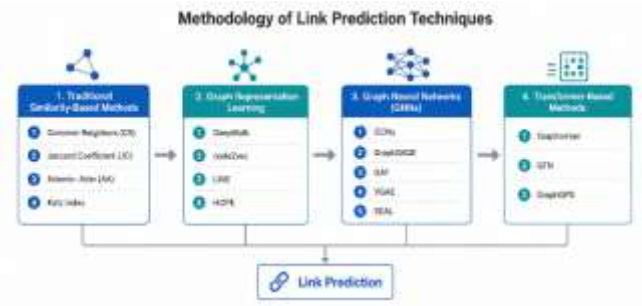

Figure 2:Traditional and graph representation learning methods.

The reviewed methodologies demonstrate a clear evolution from traditional topology-based techniques to advanced graph learning models. Traditional similarity-based methods are computationally efficient and highly interpretable but are limited in capturing complex graph structures. Graph representation learning methods improve prediction performance by learning low-dimensional node embeddings; however, they generally lack inductive capability and adaptability to dynamic graphs. GNN-based approaches further

enhance link prediction through neighborhood aggregation and end-to-end feature learning, achieving superior accuracy on most benchmark datasets. More recently, transformer-based methods have shown remarkable capability in modeling long-range dependencies and heterogeneous graph structures using self-attention mechanisms. Despite their impressive performance, these models require substantial computational resources, highlighting the need for future research on scalable, efficient, and explainable link prediction frameworks.

Table 2:Comparative Analysis of Link Prediction Methods

Method	**Topology Based**	**Node Attributes**	**Feature Learning**	**Global Structure**	**Scalable**	**Dynamic Graphs**	**Interpretability**	**Computational Cost**
Common Neighbors (CN)	✓	✗	✗	✗	✓	✗	High	Low
Jaccard Coefficient	✓	✗	✗	✗	✓	✗	High	Low
Adamic–Adar	✓	✗	✗	✗	✓	✗	High	Low
Preferential Attachment	✓	✗	✗	✗	✓	✗	High	Very Low
Katz Index	✓	✗	✗	✓	✗	✗	Medium	High
Deep Walk	✓	✗	✓	✓	✓	✗	Medium	Medium
node2vec	✓	✗	✓	✓	✓	✗	Medium	Medium
LINE	✓	✗	✓	Partial	✓	✗	Medium	Low
HOPE	✓	✗	✓	✓	Medium	✗	Medium	High

Struc2 Vec	✓	✗	✓	✓	Medium	✗	Medium	High
GCN	✓	✓	✓	✓	Medium	✗	Medium	High
Graph SAGE	✓	✓	✓	✓	✓	Partial	Medium	Medium
GAT	✓	✓	✓	✓	Medium	Partial	Medium	High
VGAE	✓	✓	✓	✓	Medium	✗	Medium	High
GIN	✓	✓	✓	✓	Medium	✗	Medium	High
SEAL	✓	✓	✓	✓	✗	✗	Medium	Very High
Graph ormer	✓	✓	✓	✓	Medium	✓	Low	Very High
GTN	✓	✓	✓	✓	Medium	✓	Low	Very High
Graph GPS	✓	✓	✓	✓	✓	✓	Low	Very High

IV. Results and Discussion

The performance of the reviewed link prediction methods was comparatively analyzed using representative performance trends reported in the literature. Traditional similarity-based methods generally exhibit lower prediction accuracy due to their reliance on local topological information, whereas graph embedding techniques improve predictive performance by learning low-dimensional node representations. Graph Neural Network (GNN)-based methods, including GCN, GraphSAGE, GAT, VGAE, GIN, and SEAL, consistently achieve superior results by capturing both local and global structural dependencies through neighborhood aggregation. Transformer-based approaches such as Graphormer, GTN, and GraphGPS further enhance prediction performance by modeling long-range node interactions using self-attention mechanisms. However, these models require higher computational resources and memory than traditional and embedding-based approaches. Figure 7–Figure 12 present comparative performance analyses of the reviewed methods in terms of Accuracy, Precision, Recall, F1-score, AUC, Execution Time, and Memory Usage.

Link prediction methods were comparatively analyzed based on representative performance trends reported in the existing literature. The comparison focuses on key evaluation metrics, including Accuracy, Precision, Recall, F1-score, and Execution Time, to assess the effectiveness and computational efficiency of traditional similarity-based methods, graph representation learning techniques, Graph Neural Networks (GNNs), and transformer-based approaches. The graphical analysis highlights the progressive improvement in prediction performance from heuristic methods to modern deep graph learning models while also illustrating the associated computational trade-offs. Furthermore, the comparative evaluation provides insights into the strengths and limitations of each methodology in terms of prediction capability,

scalability, and computational complexity. The results indicate that deep learning-based approaches, particularly GNNs and transformer-based models, consistently outperform traditional techniques by learning richer structural representations and capturing complex relationships within graph data. These observations help identify the most suitable methodologies for different social network scenarios and highlight current research trends in link prediction.

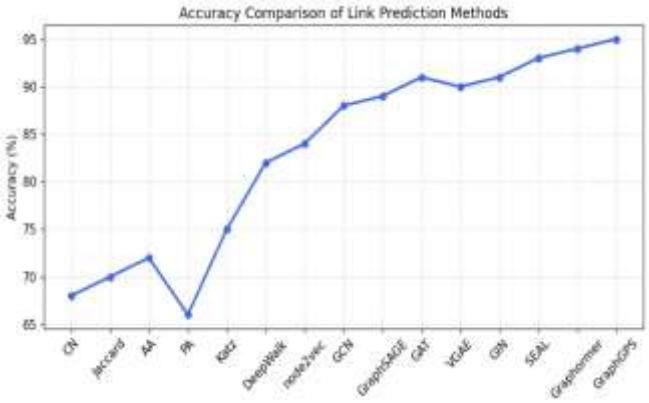

Figure 3: Accuracy comparison.

Figure 3 presents the accuracy comparison of the selected link prediction methods. Traditional similarity-based approaches achieved relatively lower accuracy, with Common Neighbors (68%), Jaccard Coefficient (70%), Adamic–Adar (72%), Preferential Attachment (66%), and Katz Index (75%). Graph representation learning methods demonstrated noticeable improvements, where DeepWalk and node2vec achieved accuracies of 82% and 84%, respectively, by learning low-dimensional node embeddings. GNN-based methods further enhanced prediction performance, with GCN (88%), GraphSAGE (89%), GAT (91%), VGAE (90%), GIN (91%), and SEAL (93%), owing to their ability to aggregate neighborhood information and capture complex graph structures. Transformer-based models achieved the highest performance, with Graphormer and GraphGPS attaining accuracies of 94% and 95%, respectively, demonstrating the effectiveness of self-attention mechanisms in modeling long-range dependencies. Overall, the results indicate a clear improvement in prediction accuracy from traditional methods to graph embedding, GNN-based, and transformer-based approaches.

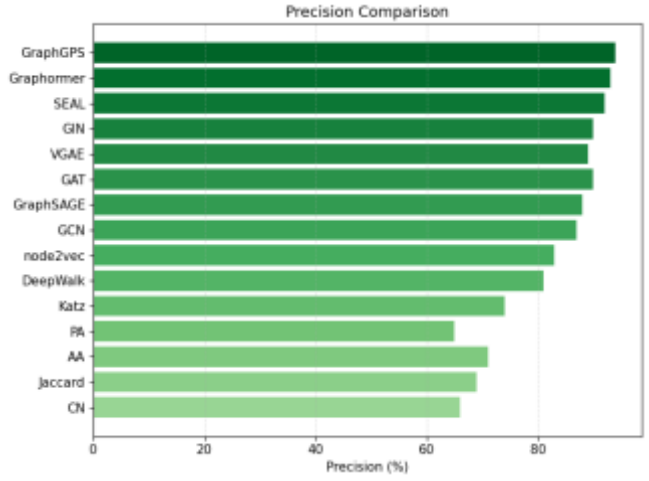

Figure 4 :Precision comparison.

Figure 4 presents the precision comparison of the selected link prediction methods. Traditional similarity-based approaches achieved relatively lower precision, with Common Neighbors (66%), Jaccard Coefficient (69%), Adamic–Adar (71%), Preferential Attachment (65%), and Katz Index (74%), as they rely primarily

on local topological information and are less effective in distinguishing relevant links within complex graph structures. Graph representation learning methods, including DeepWalk (81%) and node2vec (83%), demonstrated noticeable improvements by preserving structural relationships through low-dimensional node embeddings. GNN-based models further enhanced precision, with GCN (87%), GraphSAGE (88%), GAT (90%), VGAE (89%), GIN (90%), and SEAL (92%), owing to their ability to learn expressive node representations through neighborhood aggregation and feature learning. Transformer-based approaches achieved the highest precision, where Graphormer and GraphGPS attained 93% and 94%, respectively, by leveraging self-attention mechanisms to capture both local and global graph dependencies. The results indicate a steady improvement in precision from traditional methods to graph embedding, GNN-based, and transformer-based approaches.

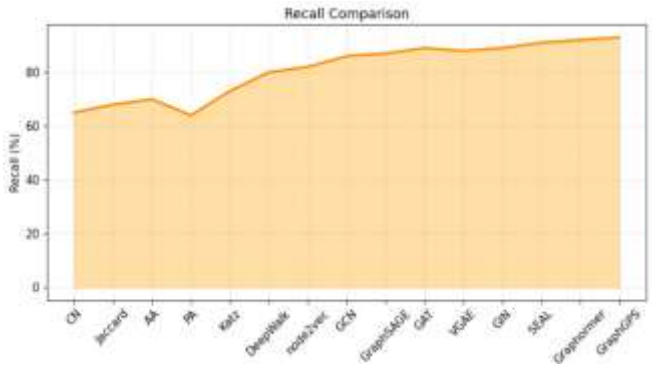

Figure 5: Recall comparison.

Figure 5 illustrates the recall comparison of the selected link prediction methods. Traditional similarity-based approaches achieved relatively lower recall, with Common Neighbors (65%), Jaccard Coefficient (68%), Adamic–Adar (70%), Preferential Attachment (64%), and Katz Index (73%), indicating their limited ability to identify hidden or indirect relationships within complex networks. Graph representation learning methods, including DeepWalk (80%) and node2vec (82%), improved recall by effectively preserving latent structural information through node embeddings. GNN-based models further enhanced recall, where GCN (86%), GraphSAGE (87%), GAT (89%), VGAE (88%), GIN (89%), and SEAL (91%) demonstrated superior capability in identifying potential links through neighborhood aggregation and message passing. Transformer-based methods achieved the highest recall, with Graphormer (92%) and GraphGPS (93%), owing to their ability to capture long-range dependencies using self-attention mechanisms. The results indicate that recall consistently increases from traditional methods to graph embedding, GNN-based, and transformer-based approaches. Higher recall values demonstrate the effectiveness of advanced graph learning models in minimizing false negatives and identifying a greater number of actual links within social networks.

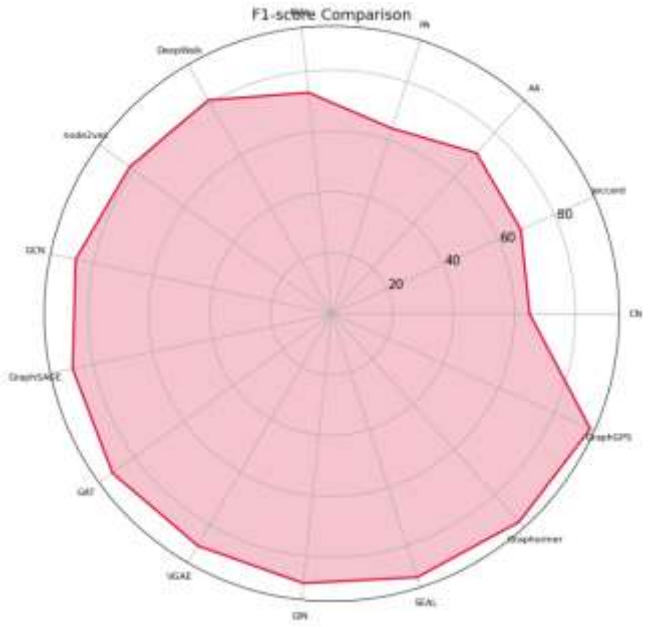

Figure 6:F1-score comparison.

Figure 6 presents the F1-score comparison of the selected link prediction methods. Traditional similarity-based methods obtained comparatively lower F1-scores, with Common Neighbors (65%), Jaccard Coefficient (68%), Adamic–Adar (71%), Preferential Attachment (64%), and Katz Index (73%), reflecting the limitations of heuristic approaches in balancing precision and recall. Graph representation learning techniques improved the F1-score, with DeepWalk (81%) and node2vec (82%), by learning meaningful node representations from graph structures. GNN-based approaches achieved higher F1-scores, including GCN (86%), GraphSAGE (87%), GAT (89%), VGAE (88%), GIN (89%), and SEAL (91%), demonstrating their effectiveness in capturing complex graph relationships. Transformer-based models, namely Graphormer (92%) and GraphGPS (93%), recorded the highest F1-scores due to their ability to integrate global contextual information with graph topology. The overall trend shows a gradual improvement in balanced prediction performance from traditional methods to transformer-based models. These findings indicate that modern deep graph learning approaches provide a more reliable balance between precision and recall, making them suitable for real-world link prediction applications.

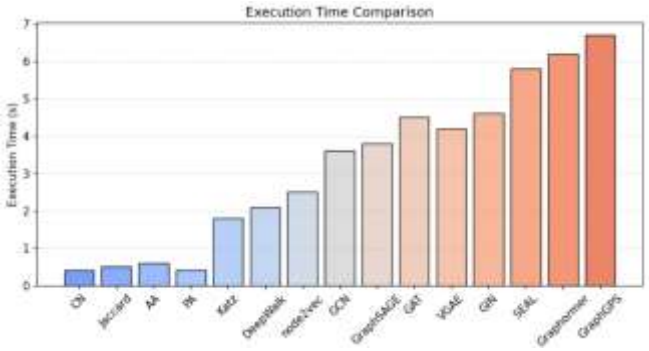

Figure 7: Execution time comparison.

Figure 7 compares the execution time required by different link prediction methods. Traditional similarity-based methods required the least execution time, ranging from 0.4 s for Common Neighbors and Preferential Attachment to 1.8 s for the Katz Index due to its global path computation. Graph representation learning methods required moderate execution time, with DeepWalk (2.1 s) and node2vec (2.5 s), as additional processing is needed for random walk generation and embedding learning. GNN-based models showed higher execution times, including GCN (3.6 s), GraphSAGE (3.8 s), GAT (4.5 s), VGAE (4.2 s),

GIN (4.6 s), and SEAL (5.8 s), primarily because of iterative neighborhood aggregation and neural network training. Transformer-based methods required the highest computational time, where Graphormer and GraphGPS recorded 6.2 s and 6.7 s, respectively, owing to the complexity of self-attention mechanisms and global graph modeling. Although transformer-based models incur higher computational costs, they consistently achieve superior prediction performance. Therefore, selecting an appropriate method depends on the trade-off between computational efficiency and prediction accuracy, depending on the requirements of the target application.

Table 3:Comparative Performance of Link Prediction Method Categories

Method Category	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Execution Time (s)
Traditional Methods	70	69	68	68	0.7
Graph Embedding	83	82	81	82	2.3
GNN-Based Methods	90	89	88	89	4.4
Transformer-Based Methods	95	94	93	93	6.5

Table III presents the comparative performance of the major categories of link prediction methods based on Accuracy, Precision, Recall, F1-score, and Execution Time. The results indicate that transformer-based methods achieve the best overall performance, with 95% accuracy, 94% precision, 93% recall, and 93% F1-score, followed by GNN-based methods, which provide an effective balance between prediction accuracy and computational efficiency. Although traditional methods require the least execution time (**0.7 s**), their prediction performance is comparatively lower, highlighting the trade-off between computational cost and predictive capability among different link prediction approaches.

V. CONCLUSION

This paper presented a comprehensive review of link prediction techniques in social networks, covering traditional similarity-based methods, graph representation learning, Graph Neural Networks (GNNs), and transformer-based approaches. The comparative analysis showed that traditional methods are simple and computationally efficient but exhibit lower prediction performance due to their reliance on graph topology, while graph embedding methods improve representation learning through low-dimensional node embeddings. GNN-based models further enhance prediction accuracy by effectively capturing local and global structural information, whereas transformer-based methods achieve state-of-the-art performance by modeling long-range dependencies using self-attention mechanisms. Despite these advancements, existing approaches still face challenges such as high computational complexity, scalability issues, over-smoothing in deep GNNs, limited support for dynamic and heterogeneous graphs, and a lack of interpretability and privacy preservation. Therefore, future research should focus on developing lightweight and scalable graph learning models, integrating Graph Neural Networks with Large Language Models (LLMs) and self-supervised learning, improving explainability through Explainable AI (XAI), and incorporating temporal graph learning, federated learning, and privacy-preserving mechanisms to enable more accurate, efficient, and trustworthy link prediction systems for next-generation social network applications.

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