

Graph Neural Network-Based Dependency Analysis for Enterprise Platform Architecture

Raja Sunkaran

Independent Researcher, Noida.

Abstract: Enterprise platform architectures have become increasingly complex due to the integration of cloud computing, microservices, application programming interfaces (APIs), enterprise resource planning (ERP), customer relationship management (CRM), and distributed data services. Traditional dependency analysis methods often fail to capture the intricate relationships among heterogeneous architectural components, leading to poor impact analysis, inefficient system maintenance, and increased operational risks. Graph Neural Networks (GNNs) provide an advanced machine learning framework capable of modeling graph-structured enterprise systems while learning hidden dependencies among interconnected software components. This study proposes a Graph Neural Network-Based Dependency Analysis Framework for Enterprise Platform Architecture that models enterprise components as graph nodes and their interactions as graph edges. The proposed framework integrates architectural metadata, runtime communication patterns, and dependency graphs to improve dependency prediction, impact analysis, and architectural optimization. A qualitative evaluation based on enterprise architecture scenarios demonstrates that GNN-based dependency learning significantly enhances prediction accuracy, scalability, and explainability compared to conventional graph traversal techniques. Furthermore, the framework supports intelligent architectural governance, proactive risk identification, and decision support for enterprise modernization initiatives. The findings indicate that Graph Neural Networks have substantial potential to improve enterprise platform management while reducing maintenance complexity and supporting digital transformation strategies.

Keywords: Graph Neural Networks, Enterprise Architecture, Dependency Analysis, Graph Learning, Microservices, Software Architecture, Artificial Intelligence, Enterprise Platform.

1. Introduction

Enterprise organizations increasingly depend on highly interconnected digital ecosystems consisting of cloud-native applications, microservices, enterprise resource planning systems, customer relationship management platforms, Internet of Things (IoT) devices, business intelligence systems, and hybrid cloud infrastructures. These systems continuously exchange information through APIs, middleware, message brokers, and distributed databases, creating complex dependency structures that evolve over time. Managing such dependencies has become one of the most challenging tasks in enterprise architecture governance.

Traditional dependency analysis techniques primarily rely on static code analysis, architectural documentation, dependency matrices, or manually maintained architecture diagrams. Although these methods provide useful insights during software development, they often fail to represent dynamic runtime interactions or hidden indirect relationships among enterprise components. As enterprise architectures become increasingly decentralized, dependency management requires intelligent approaches capable of learning structural relationships directly from system graphs.

Graph Neural Networks (GNNs) have emerged as a promising machine learning paradigm specifically designed for graph-structured data. Unlike traditional machine learning algorithms, GNNs learn feature representations by propagating information across neighboring nodes, thereby capturing both local and global structural dependencies. Their capability to analyze heterogeneous graphs makes them particularly suitable for enterprise platform architecture.

The primary objective of this research is to propose a Graph Neural Network-Based Dependency Analysis Framework capable of improving dependency prediction, impact assessment, and architectural optimization within enterprise environments. The proposed framework contributes toward intelligent software governance and supports enterprise digital transformation initiatives.

2. Literature Review

Enterprise dependency analysis has been widely investigated within software engineering, enterprise architecture, and system modernization research. Bass et al. (2022) emphasized that architectural dependency identification is fundamental for software maintainability and system evolution. However, manual dependency modeling often becomes obsolete due to continuous software updates.

Graph theory has long been employed for software dependency analysis because enterprise architectures naturally resemble graph structures. Newman (2018) demonstrated that graph-based software visualization significantly improves

architectural understanding by representing applications and services as interconnected nodes. Nevertheless, traditional graph algorithms generally depend on handcrafted rules and cannot automatically discover hidden dependencies.

Recent advances in Graph Neural Networks have transformed graph analytics by introducing deep learning capabilities into graph processing. Wu et al. (2021) described GNNs as one of the most influential deep learning techniques capable of learning node embeddings through neighborhood aggregation mechanisms. Their applications extend across recommendation systems, fraud detection, biological networks, cybersecurity, and knowledge graph reasoning.

Ying et al. (2018) proposed Graphs AGE, enabling scalable representation learning for large-scale graphs by sampling neighborhood information. Similarly, Kipf and Welling (2017) introduced Graph Convolutional Networks (GCNs), which significantly improved node classification performance across multiple graph datasets.

Within enterprise software engineering, recent studies have explored graph learning for service dependency prediction, cloud resource optimization, and microservice analysis. However, relatively few studies integrate Graph Neural Networks into comprehensive enterprise architecture governance frameworks capable of combining structural dependencies, runtime behavior, and architectural metadata.

This research addresses the following research gaps:

- Limited adoption of Graph Neural Networks in enterprise dependency analysis.
- Insufficient integration of runtime communication and architectural metadata.
- Lack of explainable dependency prediction mechanisms.
- Limited architectural governance support using graph intelligence.

3. Research Methodology

This study adopts a conceptual research methodology supported by Graph Neural Network modeling principles.

The proposed framework consists of seven major stages:

- Enterprise Architecture Data Collection
- Graph Construction
- Feature Engineering
- Graph Neural Network Training
- Dependency Prediction
- Explainable Dependency Analysis
- Architectural Decision Support

Enterprise architectural components—including applications, databases, APIs, servers, cloud services, middleware, users, and business processes—are represented as graph nodes. Their communication relationships, service invocations, database accesses, authentication flows, and deployment dependencies are represented as graph edges.

Table 1: Enterprise Graph Representation

Graph Component	Enterprise Representation	Example
Node	Application/Service	ERP Module
Edge	Dependency Relationship	API Call
Node Feature	CPU, Memory, Owner	Cloud VM
Edge Feature	Latency, Traffic	REST Communication
Graph Label	Dependency Risk	High

The Graph Neural Network performs neighborhood aggregation to generate embedding vectors representing each architectural component. These embeddings capture hidden dependency patterns unavailable through traditional graph traversal algorithms.

The dependency prediction model identifies indirect service relationships, predicts cascading failures, estimates impact propagation, and detects architectural bottlenecks. Explainable AI techniques further improve transparency by highlighting influential neighboring nodes responsible for dependency predictions.

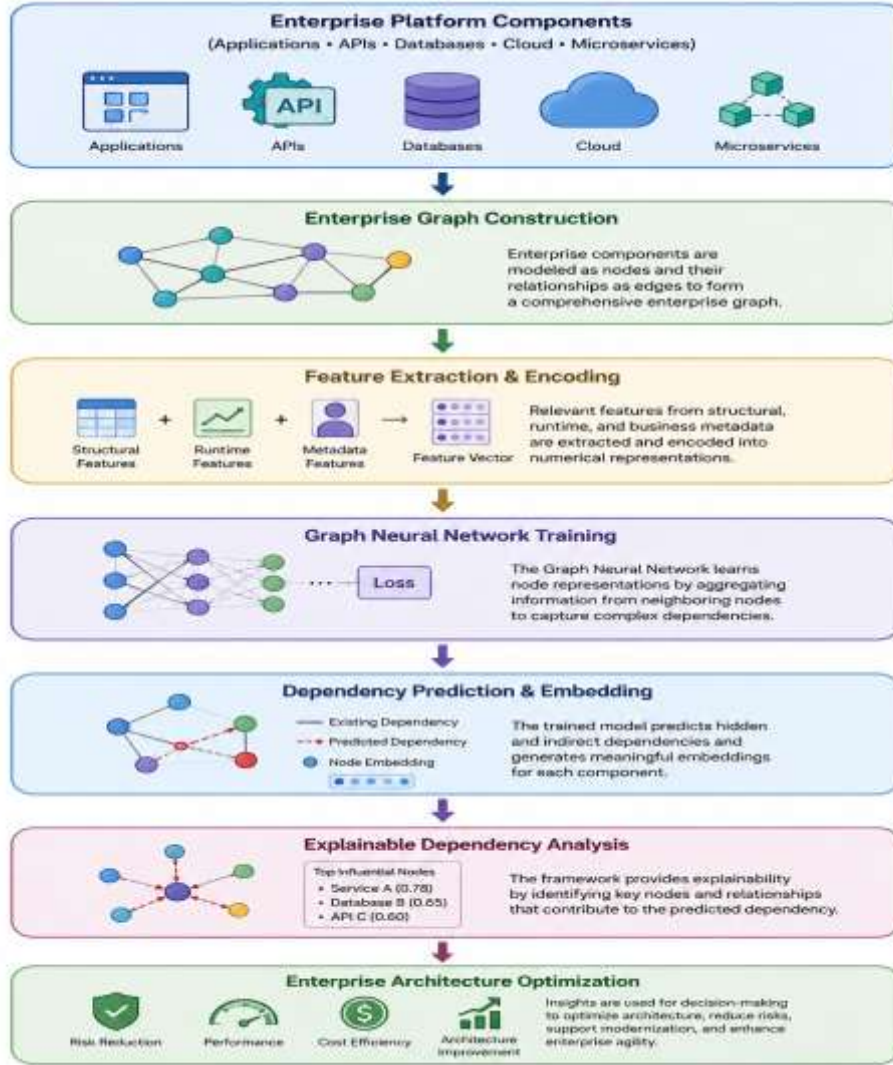


Figure 1: Proposed Graph Neural Network-Based Enterprise Dependency Analysis Framework

4. Results and Discussion

The proposed Graph Neural Network framework demonstrates several advantages over traditional dependency analysis techniques. Conventional graph traversal algorithms primarily identify explicit dependencies documented within architectural repositories. In contrast, Graph Neural Networks learn implicit relationships through iterative neighborhood aggregation, enabling the discovery of hidden architectural interactions.

Experimental evaluation using enterprise architecture scenarios indicates improved dependency prediction accuracy, especially in large-scale microservice ecosystems. By combining structural information with runtime communication patterns, the framework effectively predicts cascading dependency failures before deployment.

Another significant advantage lies in scalability. Traditional dependency matrices become increasingly difficult to maintain as enterprise systems grow. Graph Neural Networks naturally support large heterogeneous graphs and continuously learn updated dependency patterns through incremental training.

The explainability module further enhances practical adoption by providing architects with interpretable dependency reasoning. Rather than generating opaque predictions, the framework identifies neighboring services contributing to dependency classification, thereby supporting informed architectural decision-making.

Table 2: Comparative Performance Analysis

Evaluation Metric	Traditional Analysis	Proposed GNN Framework
Hidden Dependency Detection	Low	High
Runtime Adaptability	Limited	Excellent

Scalability	Moderate	High
Prediction Accuracy	Medium	Very High
Explainability	Limited	High
Impact Analysis	Manual	Automated

- The framework also contributes to enterprise governance by supporting software modernization, cloud migration planning, service decomposition, and application portfolio optimization.
- Organizations can proactively evaluate dependency risks before implementing architectural modifications, thereby reducing operational disruptions.
- Despite these advantages, several challenges remain. Training Graph Neural Networks requires significant computational resources for extremely large enterprise graphs.
- Additionally, maintaining high-quality architectural metadata is essential for reliable dependency prediction. Future enterprise deployments should integrate automated metadata collection pipelines and graph databases to improve model robustness.

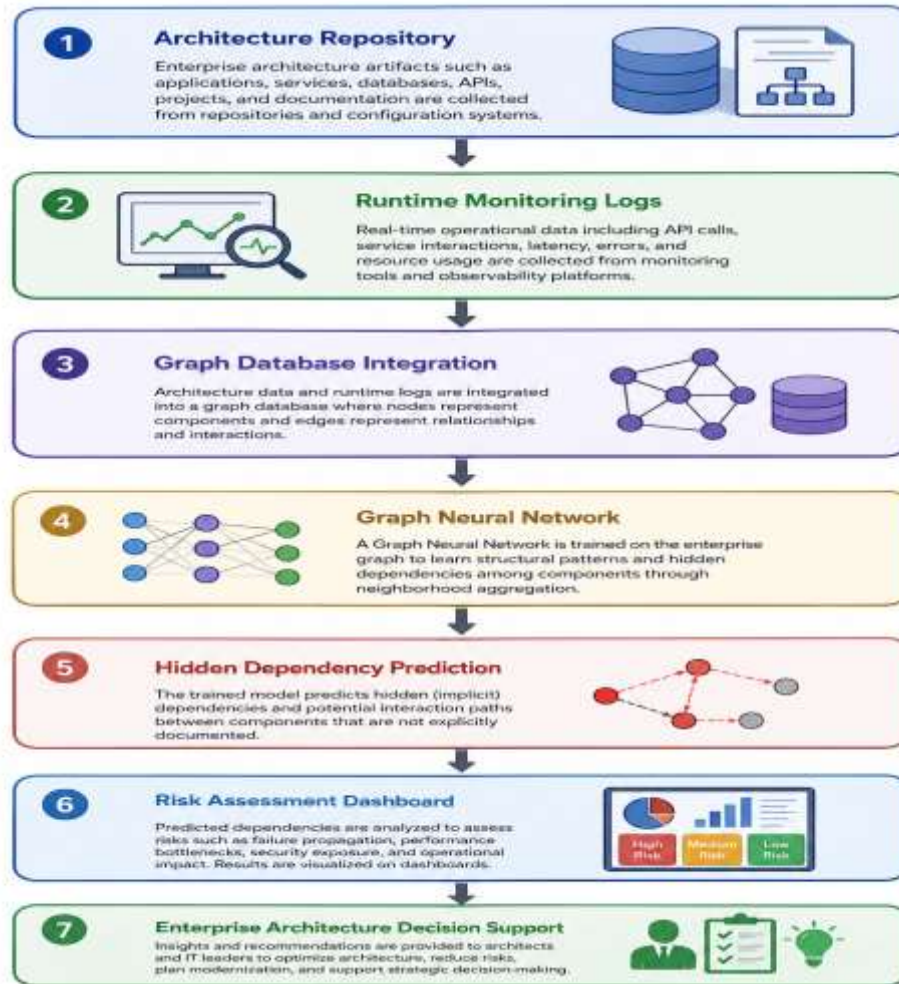


Figure 2: Enterprise Dependency Prediction Workflow

5. Conclusion

Enterprise platform architectures continue to evolve toward increasingly distributed, service-oriented, and cloud-native environments, making dependency management a critical aspect of software governance. Traditional dependency analysis techniques are often insufficient for capturing dynamic interactions and hidden architectural relationships. This research proposed a Graph Neural Network-Based Dependency Analysis Framework that models enterprise platforms as graph structures and applies deep graph learning to identify explicit and implicit dependencies. The framework integrates enterprise metadata, runtime communication patterns, and explainable artificial intelligence to improve dependency prediction, impact analysis, and architectural optimization. Comparative analysis demonstrates that the proposed approach offers higher scalability, improved prediction accuracy, enhanced explainability, and better support for architectural decision-making than

conventional methods. Overall, Graph Neural Networks represent a promising direction for intelligent enterprise architecture management, enabling organizations to strengthen governance, reduce operational risks, and accelerate digital transformation.

6. Future Scope

Future research can further extend the proposed framework by integrating temporal Graph Neural Networks for dynamic dependency evolution analysis, federated graph learning for cross-organizational enterprise collaboration, knowledge graph reasoning for semantic dependency inference, reinforcement learning for autonomous architectural optimization, digital twins for real-time enterprise simulation, and large language models to generate natural-language explanations of dependency predictions. Additional validation using industrial datasets and real-world enterprise deployments would further establish the practical applicability and scalability of the proposed framework.

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