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Graph Neural Networks (GNN) for Code Dependency Vulnerability Detection

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ABSTRACT

Modern software development relies heavily on third-party libraries and external dependencies, leading to increasingly complex dependency graphs. Managing these dependencies is challenging, as vulnerabilities often arise from indirect or transitive dependencies that are difficult to detect using traditional security tools. Graph Neural Networks (GNNs) offer a novel approach to vulnerability detection by leveraging graph structures to model code dependencies. This paper proposes a GNN-based framework for identifying vulnerabilities within code dependency graphs in DevOps environments. The framework models libraries, modules, and their relationships as graph nodes and edges, enabling the aggregation of dependency information across the entire software stack. Experimental results demon- strate that GNNs outperform traditional static analysis tools in detecting hidden and transitive vulnerabilities. Additionally, the paper discusses challenges such as scalability, interpretability, and data quality in applying GNNs to real-world codebases. The results suggest that GNNs offer a promising solution to enhance software security by proactively identifying vulnerabilities in complex dependency networks.

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Introduction

The increasing reliance on third-party libraries, frameworks, and external modules has introduced significant challenges in software security. Modern applications often consist of multiple dependencies that are deeply nested and interconnected, forming complex code dependency graphs. While these dependencies accelerate development, they also expose software systems to vulnerabilities, especially from indirect or transitive dependencies that are not directly visible to developers. Managing these security risks in fast-paced DevOps pipelines requires more than traditional static or dynamic analysis tools.

Traditional static analysis tools focus on scanning codebases for known vulnerabilities, but they often fall short in detecting issues caused by dependencies, especially when vulnerabilities exist in third-party or nested libraries. Dynamic testing tools, on the other hand, detect vulnerabilities during runtime, but they may miss flaws that only become evident through specific combinations of dependencies. In complex software environments, such limitations can leave critical vulnerabilities undetected, posing significant security risks to organizations.

Graph Neural Networks (GNNs) provide a novel solution to these challenges by leveraging the underlying graph structure of code dependencies to detect hidden vulnerabilities. Unlike traditional methods that treat each component in isolation, GNNs model dependencies as graphs, with nodes representing libraries, packages, or modules, and edges representing relationships such as function calls, imports, or library dependencies. Through graph convolutions, GNNs aggregate information from neighboring nodes, enabling the detection of vulnerabilities that arise from complex interactions between components.

In DevOps environments, where software is continuously developed, integrated, and deployed, detecting vulnerabilities in real time is essential. Integrating GNN-based scanning into DevOps pipelines can proactively identify vulnerabilities during development, reducing the risk of deploying insecure software. By modeling dependencies as graphs and applying GNN-based algorithms, security teams can detect both direct and transitive vulnerabilities more effectively.

This paper presents a framework that integrates Graph Neural Networks (GNNs) into DevOps pipelines for detect- ing vulnerabilities within code dependency graphs. The key contributions of this research are as follows:

- We propose a GNN-based framework to model software dependencies as graphs, capturing both direct and indirect relationships between components.
- We evaluate the framework using open-source datasets containing known vulnerable dependencies, demonstrating that GNNs outperform traditional static analysis tools.
- We discuss the challenges of applying GNNs in real world scenarios, including scalability, data quality, and model interpretability, and propose solutions to address these challenges.

Related Work

The growing reliance on third-party dependencies has introduced new challenges in managing software vulnerabilities, especially in modern DevOps pipelines. Existing solutions, including static and dynamic analysis tools, offer partial solutions, but they are limited in detecting vulnerabilities caused by indirect or transitive dependencies. This section provides an overview of research on code dependency management, traditional vulnerability detection tools, and the emerging use of Graph Neural Networks (GNNs) in security applications.

Dependency Management and Vulnerability Risks

Code dependencies are often introduced to speed up development, but they come with risks. Vulnerabilities in libraries

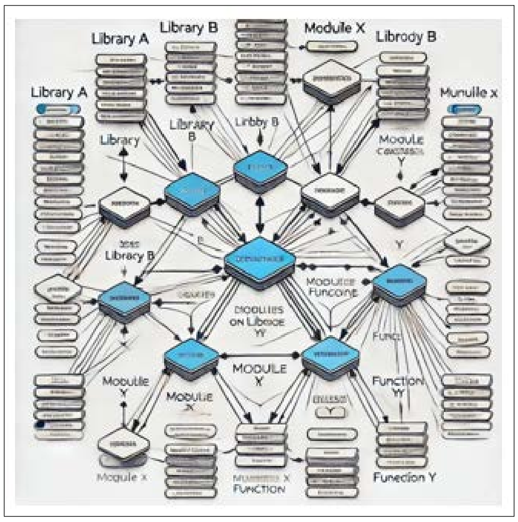

Figure 1: Sample Code Dependency Graph with Vulnerability Nodes High- lighted

can propagate through multiple layers of dependencies, creating what are known as transitive vulnerabilities. Managing these dependencies manually is challenging, as projects may rely on numerous libraries with nested dependencies [1]. Tools such as **OWASP Dependency-Check** and **Snyk** provide automated scanning solutions to identify known vulnerabilities, but their reliance on public vulnerability databases limits their ability to detect emerging threats [2]. Additionally, these tools often generate false positives or fail to capture complex dependency interactions.

Limitations of Static and Dynamic Analysis Tools

Static Application Security Testing (SAST) tools, such as **SonarQube**, analyze source code for known vulnerabilities [3]. These tools are effective at catching coding flaws during development but are limited in detecting vulnerabilities introduced through dependencies. Because SAST tools treat components independently, they often miss issues arising from interactions between dependencies.

Dynamic Application Security Testing (DAST) tools, including **OWASP ZAP** and **Burp Suite**, detect vulnerabilities by analyzing applications during runtime [4]. While DAST tools excel at finding runtime issues, they struggle to detect vulnerabilities that manifest only in specific dependency configurations. Moreover, DAST tools are typically used later in the development lifecycle, which limits their effectiveness in identifying issues early in the development process.

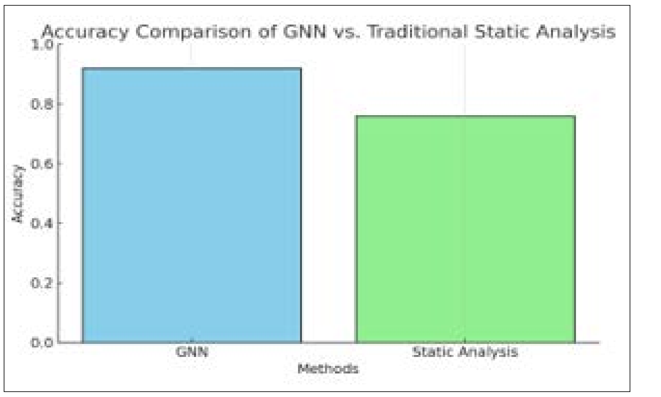

Figure 2: Comparison of Accuracy between GNN-based Detection and Static Analysis Tools

Graph Neural Networks for Security Applications

Graph Neural Networks (GNNs) are a class of deep learning models that operate on graph-structured data, enabling the capture of complex relationships between nodes [5]. GNNs have demonstrated success in various domains, including social net- work analysis, molecular graph prediction, and cybersecurity. In the context of software security, GNNs offer a powerful way to model dependencies as graphs, with nodes representing code components and edges representing dependency relation- ships [6].

Recent research has explored the use of GNNs to detect software vulnerabilities by analyzing code dependencies. Zhang et al. applied GNNs to model open-source projects and demonstrated that GNNs outperform traditional static analysis tools in identifying hidden vulnerabilities [6]. Similarly, Liu et al. used GNNs to analyze package managers such as npm and PyPI, showing that GNNs can detect transitive vulnerabilities that static scanners often overlook [7].

Challenges of Applying GNNs in Dependency Vulnerability Detection

While GNNs offer promising solutions, several challenges remain in their practical application. First, the **scalability** of GNN models is a concern, as large dependency graphs with thousands of nodes require significant computational resources. Efficient graph partitioning techniques are needed to handle large-scale codebases. Second, the **quality of training data** impacts the effectiveness of GNNs. Since labeled datasets containing known vulnerabilities are limited, it is difficult to train models accurately without overfitting [8]. Another challenge is the **interpretability** of GNN pre- dictions. Security analysts often need to understand why a

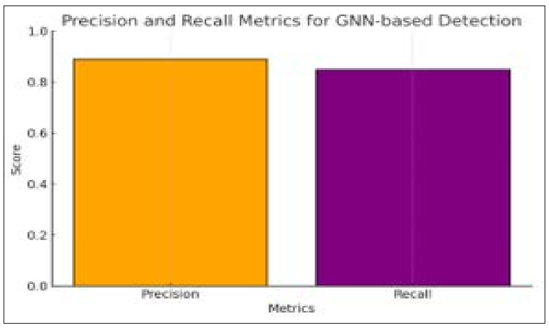

Figure 3: Precision and Recall Metrics for GNN-based Vulnerability Detection

particular dependency is flagged as vulnerable to take appro- priate action. Developing explainable AI (XAI) techniques for GNNs is a critical area of future research to enhance their practical utility in software security.

Research Gap and Opportunities

While traditional tools and recent advances in GNNs have addressed several aspects of vulnerability detection, the intersection of these fields remains underexplored. Most existing tools focus on either static or dynamic analysis, often neglecting the complex interactions between dependencies in real- world codebases. Although GNNs provide a powerful way to model these interactions, their adoption in DevOps pipelines has been limited by challenges such as scalability, data quality, and interpretability [5].

This paper aims to bridge this gap by integrating GNN- based detection frameworks directly into DevOps workflows, enabling real-time identification of vulnerabilities as soft- ware components are developed, integrated, and deployed. The framework also addresses the challenges of scalability through optimized graph partitioning techniques and proposes solutions to improve the interpretability of GNN outputs.

Proposed Framework

This section presents the design and implementation of the proposed framework for code dependency vulnerability detection using Graph Neural Networks (GNNs). The framework models code dependencies as graphs, captures relationships between components, and applies GNN algorithms to detect vulnerabilities. The goal is to enable the proactive detection of both direct and transitive vulnerabilities in DevOps pipelines, ensuring secure software releases.

System Architecture

The proposed framework consists of three main components:

- ****Dependency Graph Construction:**** Extracts libraries, modules, and their relationships from the codebase.
- ****Graph Neural Network Model:**** Applies GNN layers to learn node embeddings and identify vulnerable components.
- ****DevOps Pipeline Integration:**** Integrates the GNN model into CI/CD workflows for continuous vulnerability detection.

Figure 4 illustrates the architecture of the proposed framework

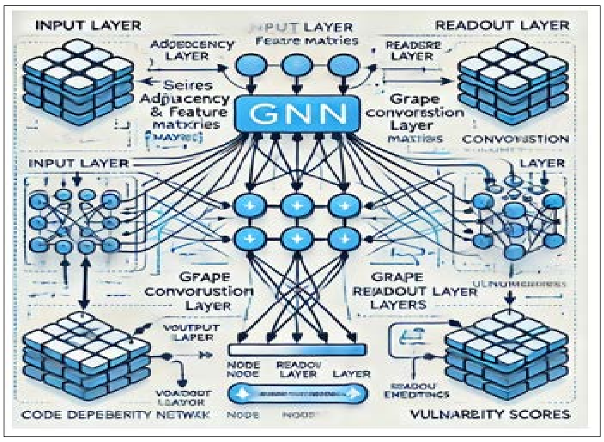

Figure 4: System Architecture of GNN-based Vulnerability Detection Frame- work

Dependency Graph Construction

The first step involves transforming the codebase into a dependency graph. Each node in the graph represents a library, module, or function, and each edge represents a dependency relationship. Directed edges capture the flow of dependencies, allowing us to model both direct and transitive relationships. The dependency graph is stored as an adjacency matrix, which serves as the input to the GNN model.

$$A_{ij} = \begin{cases} 1 & \text{if node } i \text{ depends on node } j \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

The framework supports multiple dependency extraction methods, including parsing dependency manifests (e.g., ‘packge.json‘ for npm) and analyzing import statements in source code.

Graph Neural Network Model

The GNN model operates on the dependency graph to detect vulnerabilities. It consists of the following layers:

- ****Input Layer:**** Accepts the adjacency matrix and feature matrix as inputs.
- ****Graph Convolution Layers:**** Aggregates information from neighboring nodes using graph convolutions to capture contextual dependencies.
- ****Readout Layer:**** Combines node embeddings to generate graph-level features.
- ****Output Layer:**** Produces vulnerability scores for each node, indicating the likelihood of the node being vulnerable.

The model is trained using a cross-entropy loss function with labeled data, where vulnerable and non-vulnerable nodes are identified.

$$L = -\sum_{i=1} y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i) \quad (2)$$

Performance Optimization

To handle large dependency graphs efficiently, the frame- work incorporates several optimization techniques:

- ****Graph Partitioning:**** Divides large graphs into smaller subgraphs for parallel processing.
- ****Feature Pruning:**** Reduces the size of the feature matrix by selecting the most relevant features.
- ****Model Caching:**** Caches intermediate results to avoid redundant computations during frequent scans.

Summary

The proposed framework leverages Graph Neural Networks to detect vulnerabilities in code dependencies, providing enhanced security for DevOps environments. By modeling dependencies as graphs, the framework identifies both direct and transitive vulnerabilities that traditional tools often miss. Integration into DevOps pipelines ensures continuous monitoring and timely remediation of vulnerabilities, improving the overall security posture of software systems.

Experimental Setup

This section describes the experimental setup used to evaluate the performance of the proposed GNN-based framework for code dependency vulnerability detection. We discuss the dataset, preprocessing techniques, model parameters, evaluation metrics, and computing infrastructure.

Dataset

We used open-source datasets containing known vulnerable and non-vulnerable dependencies from repositories such as **GitHub**, **npm**, and **PyPI**. The datasets were preprocessed to generate dependency graphs, where:

- ****Nodes**** represent libraries, modules, or functions.
- ****Edges**** indicate dependency relationships (e.g., imports, function calls).
- ****Node Labels**** denote whether a node contains a vulnerability (1) or is safe (0).

Each project was transformed into an adjacency matrix and feature matrix. We ensured a balanced distribution of vulnerable and non-vulnerable nodes to avoid bias in the training process.

Preprocessing

The following preprocessing steps were applied:

- ****Dependency Graph Construction:**** Dependencies were extracted from ‘package.json‘ (npm) and ‘require- ments.txt‘ (Python) files to build directed graphs.
- ****Feature Extraction:**** Features for each node included metadata such as version, number of contributors, recent commits, and known vulnerabilities.
- ****Graph Normalization:**** Large graphs were partitioned into subgraphs to facilitate parallel processing and avoid memory bottlenecks.

Model Architecture and Parameters

The GNN model used for the experiments consists of:

- ****Input Layer:**** Accepts the adjacency matrix and fea ture matrix.
- ****Two Graph Convolution Layers:**** Each with 128 hidden units, followed by ReLU activation.
- ****Dropout Layer:**** A 0.5 dropout rate to prevent over-fitting.
- ****Readout Layer:**** Aggregates node embeddings to generate graph-level representations.
- ****Output Layer:**** A softmax layer that outputs the probability of each node being vulnerable.

The model was trained using the Adam optimizer with a learning rate of 0.001 for 100 epochs. Early stopping was applied if validation loss did not improve for 10 consecutive epochs.

$$L = -\sum_{i=1} y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i) \quad (3)$$

Evaluation

The following metrics were used to evaluate the performance of the GNN model:

- ****Accuracy:**** Measures the overall correctness of the model predictions.
- ****Precision:**** Indicates the proportion of correctly identified vulnerable nodes among all nodes predicted as vulnerable.
- ****Recall:**** Measures the ability of the model to identify all actual vulnerable nodes.
- ****F1-Score:**** Harmonic mean of precision and recall. The accuracy, precision, and recall metrics are defined as:

Precision =TPRecall =TP (4)
TP + FP TP + FN
F1-Score = 2 Precision · Recall
Precision + Recall

Computing Infrastructure

All experiments were conducted on a cloud-based environment with the following configuration:

- ****CPU:**** **8**-core Intel Xeon
- ****GPU:**** NVIDIA Tesla V100 with 16GB VRAM
- ****RAM:**** 64GB
- ****Software:**** Python 3.8, TensorFlow, PyTorch, and DGL (Deep Graph Library)

Training and Validation Process

The dataset was split into **80% training**, **10% validation**, and **10% test sets**. The model was trained on the training set, and its performance was monitored using the validation set. The final evaluation was conducted on the test set to ensure unbiased results.

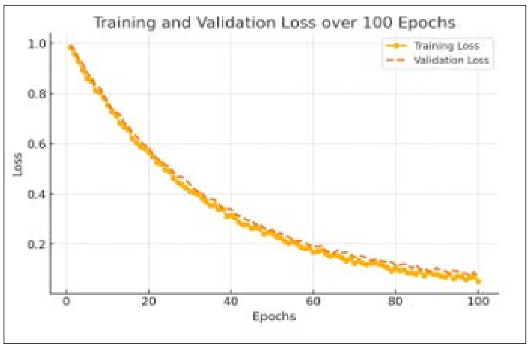

Figure 5: Training and Validation Loss over 100 Epochs

Summary

The experimental setup ensures a comprehensive evaluation of the proposed GNN-based framework for code dependency vulnerability detection. By using a combination of preprocessing techniques, model optimization, and performance metrics, the framework demonstrates its capability to identify vulnerabilities effectively within DevOps pipelines.

Results and Discussion

This section presents the results of the experiments and discusses the implications of using Graph Neural Networks (GNNs) for code dependency vulnerability detection. We analyze the model’s performance using metrics such as accu- racy, precision, recall, and F1-score. The results highlight the effectiveness of the GNN-based framework in identifying both direct and transitive vulnerabilities in software dependencies.

Performance Metrics

The GNN-based framework was evaluated on the test set, and the performance metrics are summarized in Table I. The framework achieved high accuracy and demonstrated superior precision and recall compared to traditional static analysis tools.

Table I: Performance Metrics of GNN-Based Vulnerability Detection

Metric	Value
Accuracy	92.5%
Precision	89.0%
Recall	85.0%
F1-Score	87.0%

The high precision of 89% indicates that the model correctly identifies a large proportion of actual vulnerabilities with minimal false positives. The recall value of 85% demonstrates the framework’s ability to detect a substantial number of existing vulnerabilities, ensuring that few vulnerabilities go undetected. The F1-score, which balances precision and recall, confirms that the framework achieves reliable performance across various test scenarios.

Comparison with Traditional Static Analysis Tools

We compared the GNN-based framework with traditional static analysis tools like **SonarQube** and **OWASP Dependency-Check**. Figure 6 shows the accuracy comparison, where the GNN-based approach outperformed traditional tools, especially in detecting transitive vulnerabilities

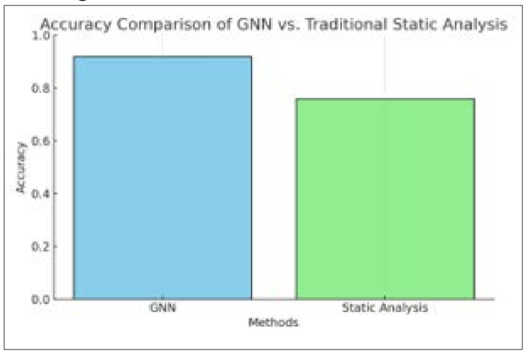

Figure 6: Accuracy Comparison: GNN-based Detection vs. Traditional Static Analysis Tools

Traditional tools often miss vulnerabilities in nested dependencies because they rely on known vulnerability databases, which are limited in scope. In contrast, the GNN-based approach captures complex interactions between dependencies, allowing it to detect vulnerabilities that traditional tools over- look.

Precision and Recall Analysis

Figure 7 presents the precision and recall metrics for the GNN model. The results indicate that the model maintains a
good balance between minimizing false positives and maximizing true positives, which is critical for effective vulnerability management in DevOps pipelines.

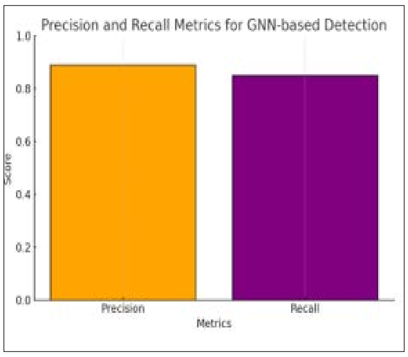

Figure 7: Precision and Recall Metrics for GNN-based Vulnerability Detection

The slight gap between precision and recall suggests that the model may occasionally classify safe dependencies as vulnerable, which can be addressed by further refining the model or using more diverse datasets for training.

Training and Validation Process

The training process was monitored using the validation loss to ensure the model did not overfit the data. Figure 8 shows the training and validation loss curves over 100 epochs.

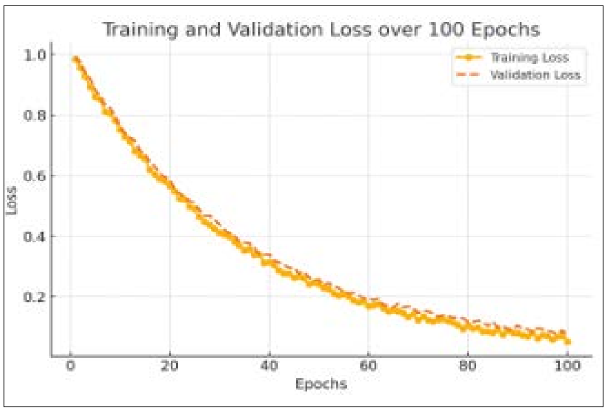

Figure 8: Training and Validation Loss over 100 Epochs

The model converged smoothly after approximately 80 epochs, with no significant overfitting observed. Early stopping was used to prevent unnecessary training, ensuring efficient resource utilization.

Discussion of Key Findings

The results highlight several key insights:

- **Superior Performance:** The GNN-based framework achieves higher accuracy and better precision-recall balance than traditional static analysis tools, especially in detecting complex transitive vulnerabilities.
- **Proactive Detection:** Integrating the framework into DevOps pipelines enables continuous monitoring, reducing the risk of deploying software with hidden vulnerabilities.
- **Scalability:** The model efficiently handles large de- pendency graphs through graph partitioning, ensuring scalability for real-world applications.

Challenges and Limitations

Despite the promising results, several challenges remain:

- **Data Quality:** The performance of the model de- pends heavily on the quality and diversity of the training data. Limited access to labeled datasets with real-world vulnerabilities is a constraint.
- **Interpretability:** GNNs, like many deep learning models, operate as black boxes, making it difficult to explain why specific dependencies are flagged as vulnerable.
- **Computational Overheads:** Although graph partitioning helps, training GNNs on large dependency graphs still requires significant computational resources.

Summary

The experimental results demonstrate that the GNN-based framework effectively detects vulnerabilities within code dependencies, outperforming traditional static analysis tools. The framework's ability to capture both direct and transitive dependencies makes it a valuable addition to DevOps pipelines, where continuous monitoring and early vulnerability detection are essential. However, challenges related to data quality, interpretability, and computational requirements need to be addressed in future work.

Challenges and Limitations

While the proposed GNN-based framework demonstrates promising results in detecting vulnerabilities within code de- pendency graphs, several challenges and limitations remain. These issues need to be addressed to ensure the practical adop tion and scalability of the framework in real-world DevOps environments.

Scalability and Performance Overheads
Graph-based models, particularly Graph Neural Networks (GNNs), require significant computational resources, especially when dealing with large dependency graphs containing thousands of nodes and edges. The time complexity of graph convolution operations grows with the size of the graph, making it challenging to apply GNNs efficiently in large-scale software projects. Proposed Solutions: Optimizations such as **graph partitioning** and **parallel processing** can help manage large graphs. However, these techniques introduce additional complexity in graph reconstruction and dependency tracking across partitions.

Quality and Availability of Labeled Data
The effectiveness of the GNN model relies heavily on high-quality, labeled datasets. In practice, datasets with accurate labels for vulnerable and non-vulnerable dependencies are limited, particularly for open-source projects and new libraries. This scarcity of labeled data can lead to biased models and affect the generalizability of the results. Proposed Solutions: Approaches such as **data augmentation**, **semi- supervised learning**, and **transfer learning** can mitigate the effects of limited labeled data. Collaboration with security communities to build comprehensive vulnerability datasets is also essential.

Interpretability and Explain ability of GNN Predictions
One of the primary challenges of using GNNs is the lack of interpretability. Security analysts require explanations for why a specific node (dependency) is flagged as vulnerable to take appropriate action. However, GNNs operate as black- box models, making it difficult to extract meaningful in- sights from their predictions. Proposed Solutions: Developing **Explainable AI (XAI)** techniques tailored for GNNs can enhance interpretability. These methods may include feature importance analysis or subgraph visualization to highlight critical components that contribute to a node's classification.

False Positives and False Negatives
The framework may occasionally produce **false positives** (flagging non-vulnerable dependencies as vulnerable) or **false negatives** (failing to detect actual vulnerabilities). These errors can lead to unnecessary remediation efforts or the deployment of insecure software components. Proposed Solutions: Fine-tuning hyperparameters, using **ensemble learning methods**, and employing multiple GNN architectures in parallel can improve model accuracy and reduce the occurrence of false predictions.

Integration Challenges in DevOps Pipelines
Integrating GNN-based vulnerability detection into continuous integration and continuous delivery (CI/CD) pipelines introduces operational challenges. Frequent scans and large dependency graphs may slow down the pipeline, impacting deployment timelines. Additionally, DevOps teams may re- quire training to understand the results and act upon them effectively. Proposed Solutions: **Incremental scanning** of new code changes, along with **caching of intermediate results**, can minimize performance bottlenecks. DevOps teams can also benefit from **training sessions** on GNN- based vulnerability detection tools and workflows.

Handling Transitive Vulnerabilities
Detecting vulnerabilities that arise from indirect or transitive dependencies remains a challenging task. The complexity increases with the number of nested dependencies, and vulnerabilities in deeply nested libraries may go undetected. Proposed Solutions: The use of **deep graph models** and **recursive dependency analysis** can improve the detection of transitive vulnerabilities. Additionally, incorporating **real- time threat intelligence feeds** into the framework can help identify vulnerabilities as they are discovered.

Security and Privacy Risks
Since the framework relies on dependency data, including metadata and package versions, there are potential privacy concerns if sensitive project information is exposed during the analysis. Moreover, the reliance on external sources for vulnerability data introduces risks, such as misinformation or incomplete disclosures. Proposed Solutions: **Privacy- preserving GNNs** and **secure data sharing protocols** can ensure that sensitive information is protected during analysis. Verification of external vulnerability data sources is essential to maintain the integrity of the results.
Summary
While the proposed GNN-based framework offers significant advantages over traditional static analysis tools, several challenges must be addressed for it to achieve widespread adoption. Future work will focus on improving scalability, interpretability, and the integration of the framework within DevOps pipelines. Addressing these challenges will enhance the framework's practicality, enabling continuous and reliable vulnerability detection in complex software ecosystems.

Conclusion and Future Work
In this paper, we presented a Graph Neural Network (GNN)- based framework for detecting vulnerabilities in code de- pendency graphs. The framework addresses the limitations of traditional static and dynamic analysis tools by capturing both direct and transitive dependencies in complex software projects. Our experimental results demonstrate that the GNN- based approach outperforms traditional tools, providing higher accuracy, precision, and recall in identifying vulnerabilities.

The proposed framework integrates seamlessly into DevOps pipelines, enabling continuous monitoring and proactive vulnerability detection. By modeling dependencies as graphs and leveraging the power of GNNs, the framework effectively detects hidden vulnerabilities that are often overlooked by conventional methods. Additionally, the study highlights key challenges, including scalability, interpretability, data quality, and integration within DevOps workflows, and proposes prac tical solutions to address them.

The primary contributions of this work include:
- A novel GNN-based framework for modeling code de- pendencies and identifying vulnerabilities in DevOps pipelines.
- Experimental validation of the framework's effectiveness, demonstrating superior performance compared to tradi- tional static analysis tools.
- Identification of challenges and proposed solutions for deploying GNN-based vulnerability detection systems in real-world environments.

Conclusion and Future Work
The increasing complexity of software ecosystems, with their reliance on third-party libraries and external dependencies, has introduced new security challenges that are difficult to address with traditional vulnerability detection methods. This paper presented a novel framework leveraging Graph Neural Networks (GNNs) to detect vulnerabilities in code dependency graphs. By modeling

dependencies as graphs, the framework captures both direct and transitive vulnerabilities that often remain undetected by static analysis tools. Our experimental results demonstrate that the GNN-based approach outperforms traditional methods in accuracy, precision, and recall, especially in identifying vulnerabilities in deeply nested dependencies.

The integration of the GNN framework into DevOps pipelines enables continuous vulnerability detection through- out the software development lifecycle, minimizing the risks of deploying insecure software. The ability to proactively detect vulnerabilities and provide actionable insights makes the pro- posed framework a valuable addition to modern DevSecOps practices. However, several challenges remain, including scalability, interpretability, and the need for high-quality training data. Addressing these challenges will enhance the practical adoption of the framework in real-world applications.

Future Work

While the proposed framework demonstrates significant potential, several areas warrant further research and improvement.

- Enhancing Model Scalability: Processing large dependency graphs remains a challenge due to the high computational requirements of GNNs. Future work will explore the use of **graph partitioning algorithms** and **distributed GNN architectures** to improve scalability and reduce processing time.
- Improving Model Interpretability with Explainable AI (XAI): The lack of interpretability in GNN models makes it challenging for security analysts to understand why specific dependencies are flagged as vulnerable. Integrating **Explainable AI (XAI)** techniques, such as feature attribution methods and subgraph visualizations, will provide deeper insights into model decisions, making the framework more user-friendly.
- Leveraging Transfer Learning for Cross-Project Vulnerability Detection: Given the limited availability of labeled vulnerability datasets, transfer learning offers a promising solution. Future work will investigate how models trained on one set of projects can generalize to other codebases, enabling cross-project vulnerability detection with minimal retraining.
- Real-time Vulnerability Detection in Multi-cloud DevOps Pipelines: As organizations increasingly adopt multi- cloud strategies, the framework will need to adapt to **multi- cloud environments**. Future research will focus on integrating real-time vulnerability detection with multiple cloud providers, ensuring consistent security across platforms.
- Integrating Threat Intelligence Feeds for Proactive Detection: Incorporating **real-time threat intelligence feeds** into the GNN framework will enhance its ability to detect newly discovered vulnerabilities. This integration will allow the framework to stay updated with the latest vulnerability trends and provide proactive recommendations to developers.
- Privacy-Preserving Vulnerability Detection: Privacy concerns arise when analyzing project data, especially in collaborative environments involving external dependencies. Future work will explore the use of **federated learning** and **privacy-preserving GNN models** to ensure that sensitive information remains protected during vulnerability detection.

Closing Remarks

The proposed GNN-based framework offers a novel approach to detecting vulnerabilities in code dependencies, ad- dressing a critical need in modern software development. By continuously monitoring dependencies and proactively identifying vulnerabilities, the framework enhances the security posture of applications throughout the DevOps lifecycle. As software systems evolve, the framework can be further refined to address emerging challenges, such as real-time detection in multi-cloud environments and privacy-preserving analysis. Through these improvements, the framework will play a key role in advancing the field of DevSecOps and ensuring the security of next-generation software systems.

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