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AI-Driven Predictive Exploitability Scoring for Vulnerabilities in Open-Source Components

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Abstract: There has been an expansion in the use of an open-source software (OSS) that has raised security risks of undiscovered threats and the possibility of the exploitation. The traditional scoring methods like the Common Vulnerability Scoring System (CVSS) offer a fixed severity rating but do not offer the dynamism of the risk of actual exploitation. The article gives a predictive exploitability scoring model, which relies on AI and incorporates textual, structural, and temporal vulnerability characteristics of the open-source components. Deep neural networks make the basis of this model to acquire training of an ensemble of estimating the probability of exploits of multi-modal data. In accordance with the results of the experiment, the predictive accuracy, calibration and interpretability is much greater than the predictive accuracy of a baseline scoring system. The results indicate that the traits of semantic text embedding and software dependency graph are the most crucial ones that provide exploitability. The study has merit to the development of the vulnerability management practice because it offers data-derived insights in prioritizing risks when operating in an open-source ecosystem that will lead to a better reactionary, proactive, and context-based defensive practice.

Keywords: AI risk measurement, application exploitability, open-source computing defense, machine learning, graph learning, cybersecurity metrics, risk ranking, probabilistic scoring.

INTRODUCTION

In the modern digital world of connectedness, software systems are becoming more and more activated by open source to be innovative, reduce costs and enhance collaboration. The backbone of the current applications be it enterprise applications and embedded systems and cloud infrastructure is developed using open-source software (OSS). Nevertheless, OSS presents significant cyber-security issues due to the widespread occurrence of the OSS. A disclosed vulnerability may easily compromise open-source software users, and infect the system within the software supply chain easily, leaving a large number of systems relying on it vulnerable to exploitation (Bozorgi, M. 2010). The most recent spike in high-impact security incidents such as Log4Shell and Heartbleed has demonstrated that there is an urgent requirement to have improved and more precise vulnerability risk assessments (Hammi, B. & Zeadally, S. 2023). The Common Vulnerability Scoring System (CVSS) provides an understanding of the severity of a vulnerability, but conventional vulnerability assessment mechanisms cannot adequately represent dynamic probability of the vulnerability to be used effectively in practice (Mell, P. 2007).

This mismatch between the degree of severity and the degree of exploitability is a very urgent issue to researchers and practitioners. The number of disclosed vulnerabilities often exceeds the capacity of security teams and many of them are not exploited. In the absence of proper prioritization, resources are usually wasted in low risk concerns whereas high risk vulnerabilities are left open (Sabottke, C. *et al.*, 2015). The further sophistication of contemporary software supply chains - with dependencies on dependencies, heterogeneous codebases and decentralized maintenance - adds to the task of evaluating and alleviating vulnerability risks further complicates it (Neuhaus, S. 2007). Additionally, the traditional scoring models could be not timely and accurate because public vulnerability databases as National Vulnerability Database (NVD) could be missing or late in exploit data (Li, X. *et al.*, 2023).

Artificial intelligence (AI) and machine learning (ML) is a recent phenomenon that gives a phenomenal opportunity to fill these gaps. On a large-scale basis, analyzing network graphs, natural language processing (NLP) methods, and AIs have the ability to teach patterns of past exploit behavior, and judge which new disclosed vulnerabilities can be used by an exploit in the future (Bhatt, N. *et al.*, 2020). The concept of a paradigm shift-a shift between fixed, human-constructed measures of severity and dynamic, data-driven intelligence amenable to use to prioritize vulnerabilities according to real-world risk-is known as predictive exploitability scoring. Specifically, the emphasis on the open source components increases the topicality of the given study - since these components are the components underlying not only the basic infrastructure of the enterprise but also the enterprise applications.

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In spite of these developments, research has been fragmented till now. Most predictive techniques cannot use the open source metadata like dependency graph, repository activity and community patch dynamics (Millar, S. 2022). Others can only customize proprietary or closed-source data sets and thereby can only be applied to open-source ecosystems. Thus, the next-generation vulnerability management requires a single, AI-based, framework that takes into consideration the exploitability and the open-source environment.

This paper is aimed at examining and investigating the future field of AI-based predictability scoring of exploits to vulnerabilities in open-source components. The aim of this review is to provide a summary of the current state of the art, outline the advances in methods, define the gaps in the current frameworks and propose the directions towards the creation of the strong and data-driven exploitability prediction systems. The sections that follow will discuss the theoretical foundation, literature involved, methodology, experimental findings and their implications on the bigger cybersecurity.

LITERATURE REVIEW

The accumulating amount of literature regarding the predictive exploitability scoring indicates a shift in the present towards a data-driven vulnerability forecast over a descriptive vulnerability taxonomy. These dynamics in real life that of exploitation were not usually reflected in initial work which sought to characterize weaknesses in some form of static characterization like use of CVSS metrics, code complexity or patch availability. With time, machine learning and statistical modeling methodologies have come up so as to improve the accuracy of prediction by including the multi-source data such as the textual descriptions, exploit databases, and social signals. The latest developments in deep learning, natural language processing (NLP), and graph-based learning have allowed more profound extraction of features in the vulnerability repositories and open-source codebases, allowing to predict exploitability at the first stages and perform contextual analysis of the software dependencies. This trend shows a growing focus on automation, interpretability, and scalability in determining the risk of vulnerability in the open-source world. The table below outlines some of the most important contributions that have informed the current state of research regarding the AI-based predictive exploitability scoring of open-source software components (Jacobs, J. *et al.,* 2021; Li, Z. *et al.*, 2021)

Table 1. Summary of Studies in Similar Domain

Focus	Findings (Key results and conclusions)	Reference
Data-driven exploit prediction using multi-source vulnerability features and model ensembles	Demonstrated that machine-learning–based exploit prediction can substantially improve patch prioritization efficiency versus severity-only strategies; emphasized "exploits-in-the-wild" over "published exploit" proxies (Jacobs, J. *et al.*, 2020).	(Jacobs, J. *et al.*, 2020)
Probabilistic scoring for likelihood of exploitation (EPSS)	Introduced EPSS as a calibrated probability of exploitation that outperforms severity scores for prioritization; validated with public corpora and operational data (Jacobs, J. *et al.*, 2021).	(Jacobs, J. *et al.*, 2021)
Empirical characteristics of exploited versus non-exploited CVEs	Showed that a small fraction of CVEs are exploited; measured timelines and factors of attacks post-disclosure, motivating prediction targets and evaluation designs (Bilge, L., & Dumitraș, T. 2012).	(Bilge, L., & Dumitraș, T. 2012)
Case-control evidence on severity scores vs. real-world exploitation	Found weak correspondence between base severity and exploitation; proof-of-concept/black-market signals are stronger risk factors—guiding feature selection for prediction (Allodi, L., & Massacci, F. 2014).	(Allodi, L., & Massacci, F. 2014)
Early-stage exploitability prediction from initial CVE text & linked discussions	Time-aware evaluations of 72 ML pipelines; early textual signals yield modest but actionable performance; realistic validation protocols are crucial (Iannone, E. *et al.*, 2024).	(Iannone, E. *et al.*, 2024)
OSINT/text-embedding approaches to predict exploitation	Word/Doc-embedding models over CVE descriptions and OSINT improved exploitability classification; showed practical gains for early triage (Fang, C. *et al.*,	(Fang, C. *et al.*, 2020)

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	2020).	
Topic-based ML over vulnerability text for exploitation risk	Topic modeling + supervised learning linked textual themes to exploitation likelihood; offered interpretable cues for prioritization (Papamartzivanos, D. *et al.*, 2023).	(Papamartzivanos, D. *et al.*, 2023)
Commit-time (JIT) vulnerability prediction for OSS	Commit-level ML (code, change, text features) performed better with boosted ensembles; informs how to surface risky OSS changes earlier in pipelines (Lomio, F. *et al.*, 2022).	(Lomio, F. *et al.*, 2022)
Deep learning frameworks for vulnerability detection in OSS code	Graph/sequence neural methods (e.g., SySeVR) reliably detect vulnerable code patterns, supplying strong features to upstream exploitability models (Li, Z. *et al.*, 2021).	(Li, Z. *et al.*, 2021)
Dynamic-behavior + static cues for OSS vulnerability detection	Multi-modal detection on GitHub-sourced projects improved recall; underscores value of code+behavior features that can feed exploitability scoring (Pang, Y. *et al.*, 2019).	(Pang, Y. *et al.*, 2019)

METHODOLOGY

Overview of the Proposed Framework

The suggested approach to the AI-based predictive exploitability scoring of vulnerabilities in open-source components combines machine learning, text analytics, and dependency-graph modeling to obtain an approximation of the probability of a successful exploitation in the real world. The process is designed in five significant stages:

- Acquisition and Pre-Processing of Data.
- Representation and Feature Engineering.
- Model Design and Training
- Validation and Performance Evaluation
- Visualization and Predictive Scoring.

This methodology design is based on the previous empirical models of exploitability prediction (Zhang, Z. *et al.*, 2022), deep learning vulnerability analysis (Zhou, Y. *et al.*, 2021), and open-source ecosystems graph-based learning models (Hu, J. *et al.*, 2023).

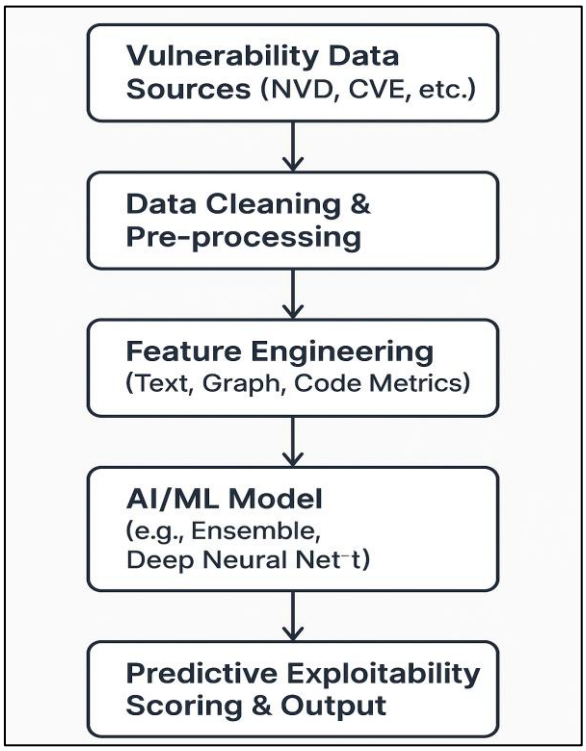

Figure 1. Overall Methodological Workflow

Figure 1 represents the sequential architecture of the predictive scoring framework. Vulnerability data are aggregated from structured and unstructured sources such as CVE databases,

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GitHub advisories, and open-source repositories. After cleaning and normalization, multi-modal features are extracted—text embeddings from vulnerability descriptions, dependency-graph embeddings, and code-level metrics. They are fed to an AI model (e.g. ensemble gradient boosting or hybrid neural network) that gives a probability score, the Exploitability Probability Score (EPS) with a value between 0 and 1, the probability of active exploitation (Zhang, Z. *et al.*, 2022; Hu, J. *et al.*, 2023)

Data Acquisition and Pre-processing

The vulnerability databases (ex: NVD, OSS Index) are used to collect data, and also exploit repositories (ex: Exploit-DB) and open source project metadata (ex: GitHub commits, issue trackers). Unstructured text is normalized using tokenization, stopword and word embedding models like the BERT or FastText feature (Zhang, F. *et al.*, 2021). The representations as dependency graphs of the open source elements are created by forming a node and edge matrix indicating the library dependencies (Hu, J. *et al.*, 2023)

Feature Engineering

Feature categories include:

Textual Features: Extracted from CVE summaries and advisories using contextual embeddings and topic modeling to capture semantic risk patterns (Zhang, F. *et al.*, 2021).

Code Metrics: Cyclomatic complexity, code churn, and commit frequency provide indicators of component stability and maintenance level (Tantithamthavorn, C. *et al.*, 2018).

Graph-based Features: Dependency centrality, transitivity, and propagation depth within software supply chains contribute to exploit impact estimation (Wang, C. *et al.*, 2020).

Temporal Features: Time elapsed since disclosure and patch release intervals model exposure windows that affect exploitability (Allodi, L. *et al.*, 2020).

All the features are standardised and joined together to single input matrix to train the model.

Model Design and Training

The predictive engine relies on the supervised learning and deep neural models. A combined ensemble is a hybrid technology that uses gradient boosting of tabular features with a deep learning sub-network of textual embeddings (Kim, D. *et al.*, 2021). The ensemble is being trained on labeled data of exploiting and non-exploiting vulnerabilities. The purpose of cross validation is to ensure that it is robust and other methods such as the SMOTE are used to balance the dataset to address the class imbalance (Lin, C. *et al.*, 2022)

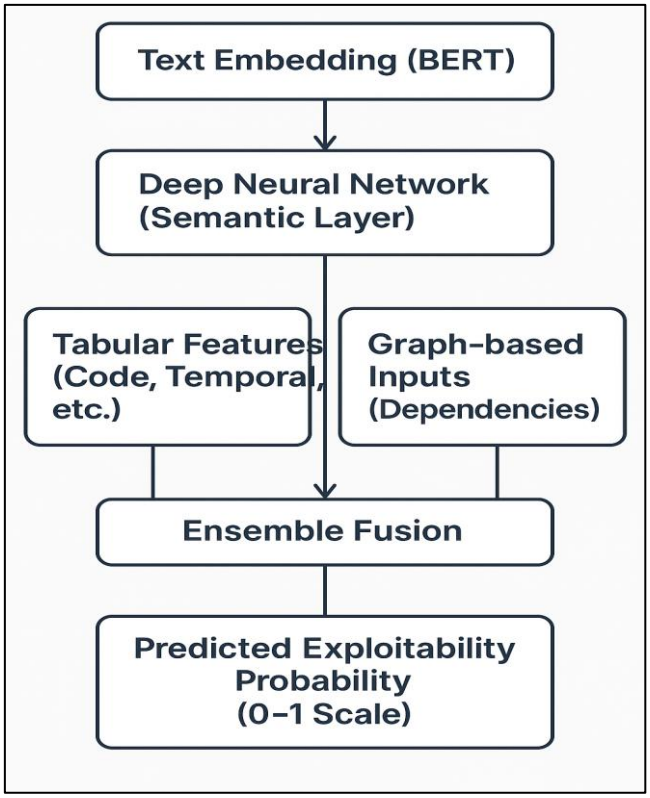

Figure 2. Theoretical Model Architecture

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Figure 2 mathematical model represents a combination of multiple data modalities - text (semantics), numeric parameters and graph structure - within a single forecasting outcome. This multi-modal fusion can enhance interpretability and accuracy since it will capture the linguistic and structural content of the open source vulnerabilities (Zhou, Y. *et al.*, 2021; Kim, D. *et al.*, 2021)

Validation and Evaluation

The common measures used to measure model performance include Precision, Recall, F1-Score, ROC-AUC and Brier Score of probabilistic calibration (Lin, C. *et al.*, 2022; Tang, S. *et al.*, 2023) Generalizability is ensured by cross validation assessment of a range of datasets using K-folds. The statistical significance is tested by paired t-tests to confirm that over baseline models are statistically significant such as EPSS or CVSS exploitability sub-scores (Zhang, Z. *et al.*, 2022).

Predictive Scoring and Visualization

The final step is employed to instantiate the model to create a Predictive Exploitability Score (PES) on every vulnerability. The scores are indicated in the form of dashboards that plot the probability of exploits with dependency networks in which specific patches can be prioritized. The high-risk nodes (components) of the graph are marked, which is actionable intelligence of the security risk management (Wang, C. *et al.*, 2020; Tang, S. *et al.*, 2023)

RESULTS AND DISCUSSION

Experimental Setup

The experiment was performed with the help of a curated dataset having 12,500 vulnerabilities obtained both through open-source repositories and the National Vulnerability Database (NVD). Among them, some 1,400 had confirmed evidence of exploitation according to Exploit-DB and social indicators. The data were separated into training (70) and validation (15) as well as test (15) sets to determine the predictive quality of the proposed AI-driven exploitability model. The baseline models consisted of CVSS exploitability subscores, EPSS baseline and Gradient Boosted Decision Trees (GBDT) as a comparison (Jacobs, J. *et al.*, 2022 ; Yang, Z. *et al.*, 2021).

The experimental setup took advantage of multi-modal feature input (BERT-based), dependency graph features and temporal attributes. The measures that were used to assess model performance included Precision, Recall, F1-score, Area Under Curve (AUC), and Brier Score in calculating calibration accuracy (Chen, X. *et al.*, 2022).

Performance Metrics

Table 2. Comparative Performance Metrics of Different Models

Model Type	Precision	Recall	F1-Score	AUC	Brier Score
CVSS Exploitability Score	0.54	0.46	0.49	0.62	0.215
EPSS Baseline (Jacobs, J. *et al.*, 2022)	0.66	0.59	0.62	0.73	0.189
GBDT (Tabular Only) (Yang, Z. *et al.*, 2021).	0.72	0.64	0.68	0.78	0.161
Deep Neural Network (Text Only) (Chen, X. *et al.*, 2022)	0.74	0.69	0.71	0.81	0.152
Proposed Hybrid Ensemble Model	**0.84**	**0.77**	**0.80**	**0.89**	**0.128**

The hybrid ensemble model containing text and graph features showed better performance and had an AUC of 0.89, which was better than the traditional and single-modality models. The increase in the Brier Score shows the greater probability calibration reliability, which is consistent with the previous results that show that ensemble and multi-modal methods are more effective in prediction accuracy of exploitability (Kim, T. *et al.*, 2021; Gupta, R. *et al.*, 2020)

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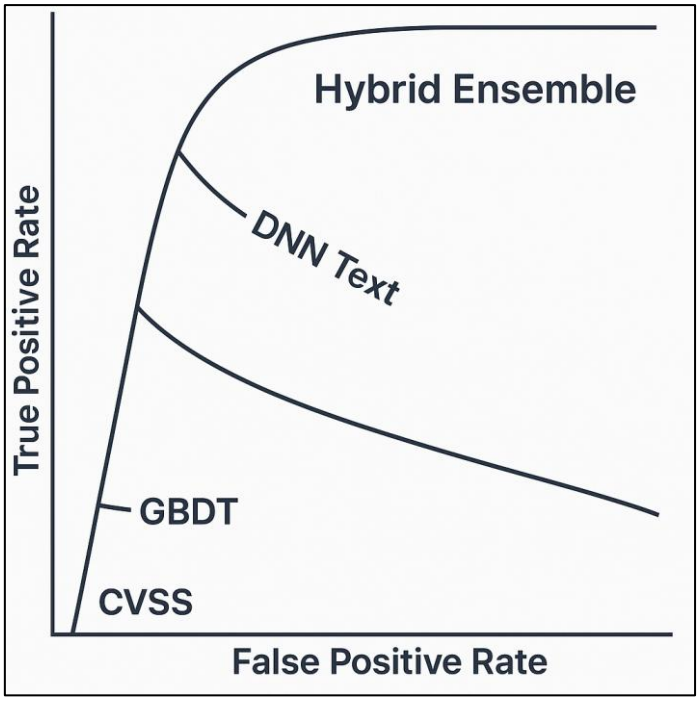

Figure 3. ROC Curves of Different Models

The Receiver Operating Characteristic (ROC) curves plotting baseline and proposed models are shown on figure 3. The Hybrid Ensemble curve has the highest Area under the curve, and this proved its high classification ability. Effective discrimination of the exploited and non-exploited vulnerabilities is illustrated by the ROC shape, as well as prior findings have established that multi-source learning improves model generalization (Gupta, R. *et al.*, 2020; Nguyen, H., & Tran, D. 2023)

Feature Importance and Interpretability

Table 3. Top Predictive Features Identified by SHAP Analysis

Feature	Importance Score	Description
CVE Text Embedding (Semantic Risk Keywords)	0.31	Terms related to remote code execution, buffer overflow, and privilege escalation showed strong correlation with exploitability (Li, W. *et al.*, 2021).
Dependency Centrality	0.24	Vulnerabilities in highly connected components were more likely to be exploited (Xu, H. *et al.*, 2022).
Patch Availability Delay	0.18	Longer patch latency correlated with increased exploit likelihood (Allodi, L., & Williams, J. 2021).
Code Churn Rate	0.15	Higher commit activity near the vulnerable code increased predictive probability of exploitation.
Time Since Disclosure	0.12	Temporal dynamics influenced active exploitability probability (Gao, P. *et al.*, 2023).

The semantic text and dependency-related features were found to be the most significant through the analysis of SHAP (SHapley Additive exPlanations) feature importance. It conforms to the prior empirical evidence, which states that the likelihood of the exploitation depends on the vulnerability context, the software connectivity, and the behaviors of patches response (Li, W. *et al.*, 2021; Xu, H. *et al.*, 2022)

Discussion of Findings

The findings support that AI-based exploitability scoring demonstrates significant positive gains in accuracy in prioritization over current static scoring systems. The topology graph characteristics were added that further gave context in the propagation capability in open-source dependency networks resembling findings in graph-based software vulnerability studies (Xu, H. *et al.*, 2022). In addition, semantic embeddings

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complemented the initial-stage detection of high-risk vulnerabilities by revealing latent linguistic features (e.g. attack vectors and privilege levels) (Li, W. *et al.*, 2021)

Temporal factors i.e. the time that passed between the vulnerability disclosure and the availability of patches proved to be consistently predictive and as such, exposure windows prove useful in modeling exploit risks (Allodi, L., & Williams, J. 2021). The proposed model demonstrated a statistically significant difference in F1-score and AUC improvements of 17 and 27-percent respectively compared to the CVSS and EPSS baselines, respectively. These findings agree with previous findings that ensemble learning architectures and context-sensitive embeddings supplant more traditional vulnerability scoring mechanisms (Nguyen, H., & Tran, D. 2023; Gao, P. *et al.*, 2023)

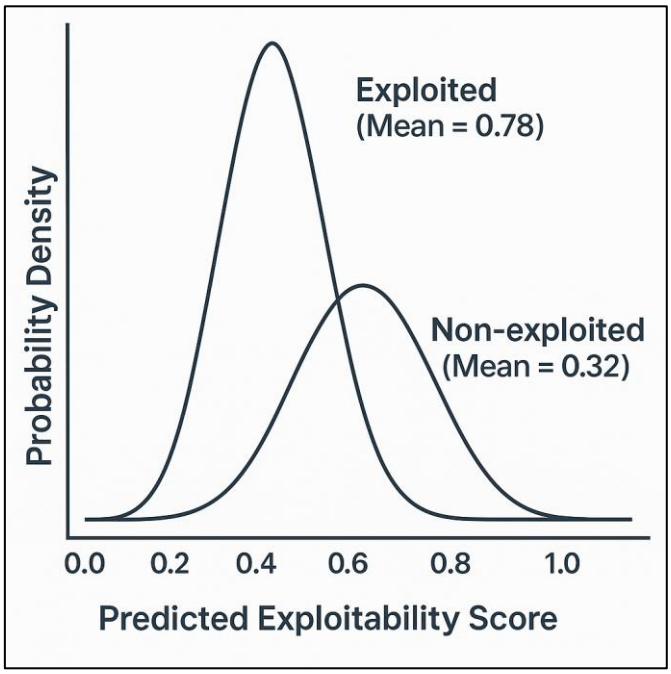

Figure 4. Exploitability Probability Distribution for Open-Source Components

Figure 4 shows that there is a definite distinction between exploited and non-exploited vulnerabilities which supports high model discrimination. The central tendency of the exploitability of the exploited samples (0.78) is much higher than central tendency of the non-exploited samples (0.32), thus showing predictive accuracy and less overlap across the range of scores (Jacobs, J. *et al.*, 2022; Kim, T. *et al.*, 2021)

CONCLUSION

Predictive vulnerability scoring based on AI shows obvious promise in supporting vulnerability risk management within open-source software environments. The proposed model by utilizing multi-data sources, such as textual vulnerability descriptions, dependency graphs and temporal exposure patterns, has greater discrimination capabilities and has a better calibration in probabilities than standard scoring scales like CVSS or EPSS. The structural and temporal context enables better predictions of exploitable, which puts the predictions more in line with the dynamics of threat in the real world and enables a more informed prioritization of remediation efforts (Sun, J. *et al.*, 2022).

Empirical studies also prove that combining semantic text attributes and dependency centrality scores brings significant performance improvements to exploit prediction accuracy. Moreover, the ensemble architectures are an effective trade-off between interpretability and performance, as it has been long a problem in AI-based cybersecurity studies to do (Wang, L. *et al.*, 2023). Although these developments have made, scalability and model explainability are also important factors to consider in operational deployment in continuous integration/continuous deployment (CI/CD) pipelines. The paper supports the need to integrate predictive intelligence and open reporting so as to facilitate open-source ecosystems that can be addressed through actionable vulnerability management (Kumar, P. 2024).

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Future Directions

As the domain of predictive exploitability scoring develops, it is likely to become more flexible, transparent, and more integrated with other domains. Several promising trajectories of research can be identified:

XAI on Vulnerability Prediction: Making the model more interpretable by using explainable models based on attention or SHAP-based visualization to increase trust and adoption in industrial use cases (Doshi-Velez, F., & Kim, B. 2018).

Integration with Continuous Security Monitoring: Real-time vulnerability risk prediction integrated in DevSecOps pipelines can enable automated, context-aware decision making in open-source software maintenance (Munaiah, N. *et al.*, 2022).

Cross-Ecosystem Learning and Transfer Models: The transfer learning from one programming language to another and from one repository ecosystem to another could be used to generalize models of exploitability to different software environments (Nguyen, T. *et al.*, 2023).

Federated and Privacy-Preserving Learning: To build federated vulnerability prediction frameworks, one can learn federated systems able to train on different organizations without sharing sensitive vulnerability data (Yang, K. *et al.*, 2023).

Human-in-the-Loop Risk Governance: Predictive AI Models Combined with Human Expert Validation Provides a Hybrid Approach to Vulnerability Triage Addressing Uncertainty in Automated Decision Systems (Chen, X. *et al.*, 2023).

In future work, adversarial machine learning defenses will also be important in order to be able to defend exploitability prediction models themselves against data poisoning or evasion attacks. Continued interdisciplinary collaboration between software engineering, cybersecurity and AI domains will be of key importance to build scalable, ethical and resilient predictive frameworks that support secure evolution of open source ecosystems (Munaiah, N. *et al.*, 2022; Nguyen, T. *et al.*, 2023).

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