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Original Article

Vulnerability Detection in Open Source Software Using Machine Learning

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Abstract:

Open Source Software (OSS) has become the pillar of modern computing, acting as the backbone to a wide variety of applications serving web platforms, embedded systems, and more. Although OSS offers innovation, cost-effectiveness, and prompt deployment, it is also vulnerable to security attacks due to its open access and community creation. A long-established approach to determining the weakness of OSS has been based on manual reviews of the code, static analysis and bug reports provided by the community. Yet, these methods can be very time-consuming and error-prone, and are not suited to the size of current OSS projects. Recently, progress in Machine Learning (ML) has opened up new possibilities for the automated and intelligent detection of vulnerabilities. With the analysis of code semantics, dependencies, and patterns in large amounts of data, it is also possible to reliably predict and classify which components are vulnerable using ML models. The current paper discusses how ML methods can be applied with the purpose of identifying vulnerabilities in OSS. These can be listed as: (i) learning the limitations of the current manual and semi-automated vulnerability detection methods, (ii) investigating the ML method of analysing source code and making use of supervised learning, deep learning, and Natural Language Processing (NLP), and (iii) determining how effective ML can be employed in OSS projects in the real world. The procedure will boil down to gathering the dataset from off-the-shelf sources (public repositories, e.g., GitHub, CVE databases), preprocessing (embedding the code into a vector), training the ML classifiers, and evaluating the performance with different levels of precision, recall, and the F1-score. Interpretability-related problems are also explored by us so that the ML-based detection could be transparent and trustworthy. Our experiments show that ML models outperform static analysis tools, achieving higher accuracy, and are faster than traditional static analysis tools. Deep learning models make use of Abstract Syntax Trees (AST) and code2vec embedding that are more effective at detecting zero-day vulnerabilities than rules-based ones. The presentation discusses the problems of imbalanced datasets, adversarial attacks on machine learning models, and explainability in security-relevant areas. The conclusion points to the demand for hybrid solutions that use ML in combination with existing static data-driven analysis to identify vulnerable OSS. Lastly, we outline future research directions, including federated learning for remote OSS communities, explainable AI (XAI) to enhance transparency, and reinforcement learning to improve adaptability in detecting vulnerabilities.

Keywords:

Open Source Software, Vulnerability Detection, Machine Learning, Deep Learning, Code Analysis, Cybersecurity.

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1. Introduction

Open Source Software (OSS) has practically changed the face of software engineering, as transparency, community, collaboration, and community-developed software have become the mechanisms driving innovation. Linux, Apache, and Kubernetes have proven their worth as popular open-source projects, providing extremely scalable, dependable, and cost-efficient solutions that are used in developing critical infrastructure, cloud platforms, and enterprise programs worldwide. The open source of OSS promotes the participation of a wide pool of developers to develop features and fix bugs faster than other non-OSS products, and this is at a lower cost to organizations that implement OSS. [1-3] Nonetheless, this transparency is a two-edged blade, because the multiplicity of authors and the horizontal management of most projects bring an endemic risk. Poor coding practices, differences in skills among contributors, laxity in quality checks, and even the absence of quality checks altogether may result in the introduction of security vulnerabilities that may not be noticed until much later. The exploitation by hostile elements may result in catastrophic effects (large scale information breaches, economic losses, loss of business and national identity in case of conflicts involving systems that cater for them at an organisation), or even have repercussions on a bigger plane such as the nation's security if the OSS is intended to support a critical national System. Given OSS's prevalent usage in multiple business sectors, the security challenge it poses is aggressive and very large-scale vulnerability identification processing must be done rapidly, automatically and on a massive scale.

1.1. Importance of Vulnerability Detection

1.1.1. Enabling Software Security

Vulnerability discovery is a key aspect of achieving secure software systems. With both open-source and proprietary being the de-facto base layer in the digital infrastructure, one non-patched hole can be an entry point for an attacker to get closer to valuable data or breaking services. Appropriate and timely detection reduces the risk issues get exploited even further -shrinks down the attack surface. If a potential security vulnerability could be weaponized, when possible, its already being detected.

1.1.2. Privacy and confidentiality of user's data

In addition to managing a large amount of professional, company's data, the complexity of software system can lead to their cascaded vulnerability that made them exploited by malicious users which can result in breaching the confidential information of an organization including illegal access, identity theft or even disclosure of sensitive data. Finding and fixing bugs systematically will also help them protect privacy on behalf of users and comply with data protection laws such as the General Data Protection Regulation (GDPR) and Health Insurance Portability and Accountability Act (HIPPA), each of which carries its own hefty penalties for negligence.

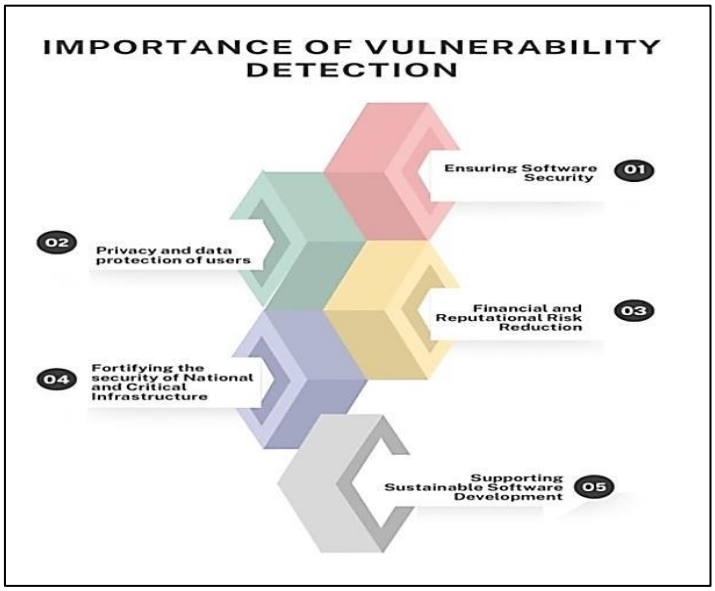

Figure 1. Importance of Vulnerability Detection

1.1.3. Risk Management

The effects of vulnerabilities are not limited to suffering a technical deficiency instead, the can result in immediate financial and reputational loss for an organisation, which is measurable. Data breaches can sometimes be super-expensive to respond to in the wake of the incident, penalties and honeymooned customer trust.

1.1.4. National and Critical Infrastructure Security –PRO-CORP

Important infrastructure, like power grids and health systems, heavily rely on open-source software, necessitating swift detection and resolution of vulnerabilities to ensure national safety and combat cyber threats.

1.1.5. Promoting Sustainable Software Development

Finding vulnerabilities in software development helps engineering last by stopping unsafe practices, lowering technical debt, and encouraging better learning about secure best practices. This leads to a strong, long-lasting software system.

1.2. Rise of Machine Learning in Security

Machine Learning (ML) is revolutionizing cybersecurity by using data-driven intelligence and pattern recognition to automatically identify vulnerabilities in complex software systems. ML models can learn unusual patterns and behaviors by training on historical data sets, identifying new threats and building on existing weak points. Open-Source Software (OSS) is dynamic, allowing for more efficient and accurate work than static and manual methods. Traditional supervised learning algorithms like Support Vector Machines (SVMs) and Random Forests solve classification problems. Deep learning models like Convolutional Neural Networks (CNNs) and Graph Neural Networks learn features considering data structure and context. Transformer-based models like CodeBERT and GPT-style architectures have improved semantic relationships and long-range dependencies, promoting automated vulnerability detection.

ML not only finds bugs but also ranks them based on their severity and ease of exploitation, aiding developers in fixing them more easily. Security also needs to be able to grow and analyze data in real time, which is why ML is growing in this area. As organizations incorporate ML-powered tools into DevSecOps pipelines, vulnerabilities may be identified at the early stages of development, thus minimize the remediation costs, and supporting the overall software security posture. Consequently, ML can no longer be conducted as an experimental method, but is on its way to becoming a pinnacle in the development of proactive, adaptive, intelligent security solutions across OSS and more.

2. Literature Survey

2.1. Traditional Vulnerability Detection Approaches

2.1.1. Traditional Static Analysis Tools (SATs)

Traditional static analysis tools (SATs), such as SonarQube and Fortify, are typically used to identify vulnerabilities by examining the source code [6-8] without executing it. They are based on preset rules and pattern-based matching to detect related problems, such as insecure coding styles, syntax errors, and well-known weaknesses, including SQL injection or buffer overflow. However, practical at identifying simple flaws, static analysis tools are not very successful at detecting more complex types of logic flaws that arise due to complicated interactions of logic in the code. In addition to this, this type of check will tend to generate a large number of false positives, and sometimes this may overwhelm the developers, thus lowering their effectiveness.

2.1.2. Dynamic Analysis

Methods of dynamic analysis test software in runtime, allowing for the identification of vulnerabilities that are revealed only after the program is put into operation. This involves finding memory leaks, race conditions, and weaknesses in dependencies on input. Dynamically analysed tools mimic a real-world situation and are therefore especially useful at detecting flaws that only manifest at runtime. However, dynamic analysis is resource-demanding, as it requires a lot of computing resources, time (which may be considerable), and a controlled environment to run the test cases. Therefore, it is not always practical on large-scale systems or with continuous integration pipelines.

2.1.3. Manual code review

Manual code review is the inspection of source code by human experts who examine the code with care in order to detect vulnerabilities. The strength of the method is that it leverages the reviewer's knowledge of the domain and their ability to comprehend complex business logic that might otherwise be missed by automated tools. It is deemed one of the surest ways of identifying slight matters that need context delivery. But manual reviewing on its own is slow, it is labor-intensive, and things can be forgotten or otherwise drop through. Besides, results can be achieved, depending greatly on the level of expertise of the reviewers, thus being less scalable in the context of contemporary software development cycles.

2.2. Approaches, Based on Machine Learning

2.2.1. Supervised Learning

With supervised machine learning, code snippets of vulnerable and non-vulnerable code are labeled to use the related dataset in training algorithms like Support Vector Machines (SVMs) and Random Forests. Such classifiers are trained on patterns

related to vulnerabilities and are in a position to generalize to similar challenges on unseen code. The supervised models have demonstrated good results where vulnerability detection can be automated with increased accuracy as compared to conventional tools, as long as there is enough labelled data to work with. However, their effectiveness can be limited by the quality and size of the training dataset, and thus, they have trouble dealing with unseen or new forms of vulnerability.

2.2.2. Deep Learning

The methods of the deep learning enhances the vulnerability detection by leveraging embeddings, to neural network architectures that models the semantic representations of the code. The Code2vec and Word2Vec can be seen as more nuanced methods, by generating the meaningful representations of the code tokens in vector space. The deep learning models can learned to identify the vulnerabilities by looking at a deeper level of semantic meaning, rather than only their syntax. These methods are representing the state of the art, but still requires a significant computational resources and an extremely large database, which can be a hindrance for smaller organizations or projects.

2.2.3. NLP-based models

NLP is intersecting with the software engineering, and the newer models analyzes the source codes as a kind of the natural language. The vulnerability detection is carried out using the transformer-based architectures, such as BERT and its many variants, to learn contextual dependencies in the code. The models are good at writing a long-range of dependencies and semantic meaning by code, thus better at making an accurate predictions than the traditional or shallow learners. Nevertheless, NLP-based solutions are more efficient and they can also faces the challenges with the model interpretability and the need for a large volume of training data to perform well.

2.3. Literature Oversights

Although the literature has advanced in both traditional and machine learning-based methods, there are still several crucial gaps that have not been addressed. [9,10] A shortage of labeled datasets can be one of the biggest limitations and hinder the process of using machine learning models as well as their training and evaluation. With publicly available datasets being small, domain-specific, and imbalanced, the insights gained from the research are limited in their applicability. A serious issue is the explainability of machine learning models, particularly deep learning models and transformer-based models. These models are also frequently treated as black boxes, and so it is not clear to the developer why a certain piece of code is labeled as vulnerable; it therefore does not foster trust and use in the real world. Besides, machine learning models are also vulnerable to adversarial attacks, in which adversarial inputs can mislead the models into incorrect classifications. This raises questions about the effectiveness and reliability of ML-powered vulnerability detection systems, with potential future research exploring the enhancement of model transparency, robustness, and access to datasets.

3. Methodology

3.1. Dataset Collection

To ensure the accuracy and reliability of flaw detection models, datasets must be collected from reliable sources like GitHub repositories, Common Vulnerabilities and Exposures (CVE) databases, and the National Vulnerability Database (NVD). These databases provide standard identifiers and information about vulnerabilities, making the metadata better for specific classification tasks.

After collecting raw data, preprocessing is performed to ensure it is of good quality and consistent for machine learning models. Tokenization, a method from studying languages, is used to split source code into smaller pieces, allowing different algorithms to look for patterns. The Abstract Syntax Tree (AST) is extracted to find structural and syntactic relationships in the code, allowing models to gain higher-level semantics. Techniques like normalization, particularly the standardization of variable and function names, are employed to achieve fundamental similarity and reduce noise. The combination of different sources, thorough preprocessing, and a structural representation of the data makes the final data complete and representative, ready to be used to train effective vulnerability detection models.

3.2. Feature Extraction

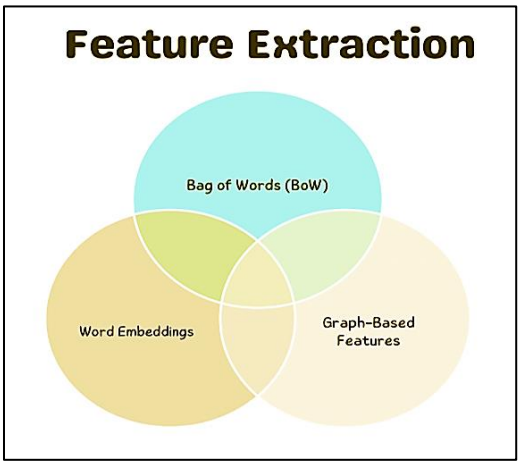

Figure 2. Feature Extraction

3.2.1. Bag of Words (BoW)

The simplest feature extraction methods for representing source code is the Bag of Words technique. It transforms code into a sequence of tokens, such as keywords, operators, and identifiers, but ignores syntax and order. The frequency of each token is then converted into a feature, which in turn provides a high-dimensional, sparse representation of the code. Although BoW proves successful in identifying the presence of vulnerable keywords or patterns, it lacks semantic interpretation and the ability to depict correlations among tokens, thereby severely restricting its efficacy in identifying complex vulnerabilities.

3.2.2. Word Embeddings

Word embedding techniques, such as Word2Vec, FastText, or code2vec, are used to capture richer information on semantic relationships. The operations convert the code tokens to high-density, low-dimensional vectors wherein the similarity between them is maintained in context. For example, semantically similar functions or identifiers will have similar vector representations, allowing models to be created that identify vulnerabilities not based on raw frequencies, but on the meaning within the code. The word embeddings are becoming highly successful in enhancing the capacity of machine learning and deep learning models to generalised to other programming styles and projects, rendering the models more powerful than BoW features.

3.2.3. Graph-Based Features

Graph-based representations build on structural information that exists in source code by representing it using Abstract Syntax Trees (ASTs), Control Flow Graphs (CFGs), or Data Flow Graphs (DFGs). These characteristics can help models retrieve hierarchical and logical dependencies between code elements, enabling them to comprehend both syntax and program flow. These structures can then be submitted to Graph Neural Networks (GNNs) and related techniques to extract complex vulnerability patterns that are not necessarily tied to lexical or contextual similarity. This method is particularly useful in detecting vulnerabilities that are based on program logic and control dependencies.

3.3. Model Development

3.3.1. Supervised Models

Large sets of traditional supervised learning models are commonly used in vulnerability detection tasks, including, among many others, Logistic Regression, Support Vector Machines (SVM) and Random Forest. [14,15] The models are trained using labeled data sets in which the snippets of the code have to be labeled as vulnerable or non-vulnerable. LR can also be used where it is desired that the results be interpretable, and we are classifying based on two classes. In contrast, SVM can effectively classify many more classes, but the use of kernels can aid in discrimination between high-dimensional data. The ensemble method (Random Forest) that uses several decision trees together to enhance robustness and minimize overfitting is appropriate in processing noisy code features. These models are comparatively lightweight and can be trained quickly, but they tend to rely strongly on the quality of handcrafted features, such as Bag of Words or token-based embeddings.

3.3.2. Deep Learning Models

The deep learning gives more effective techniques for autonomously acquiring intricate patterns in the source code, whereas the Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Graph Neural Networks (GNNs). RNNs (LSTMs and GRUs) are fine to develop the sequential dependencies used to understand the code flows. The CNNs are good at learning local patterns in tokens and syntax. GNNs are better than sequential models, because they use graph-based features

like Abstract Syntax Trees or Control Flow Graphs to find structural and semantic connections in code. These models reduce the demand to build the features by hand, and they can usually find vulnerabilities happen of complicated code dependencies.

3.3.3. Transformer Models

Source Code Analysis. The integration of transformer-based techniques as CodeBERT and GPT-style architectures, to the natural language processing research pipeline took prominence in the recent years. These models also exploit the self-attention systems to obtain long-range and semantic dependencies in code are efficient than RNNs and CNNs. Particularly, CodeBERT, which is pre-trained over large code corpora, has shown the robustness of identifying vulnerable tasks, code summarization, and defect prediction. Generative GPT-based models can also be used to help discover vulnerabilities as they can learn context-specific patterns in large repositories. Transformer models can lead to state-of-the-art performance; however, they are generally computationally expensive, and fine-tuning is often required with large labelled data sets.

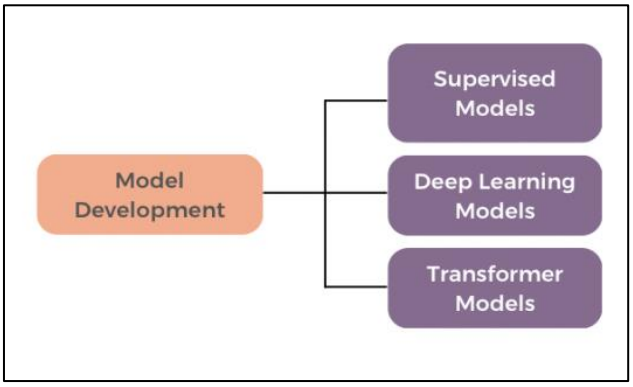

Figure 3. Model Development

3.4. Evaluation Metrics

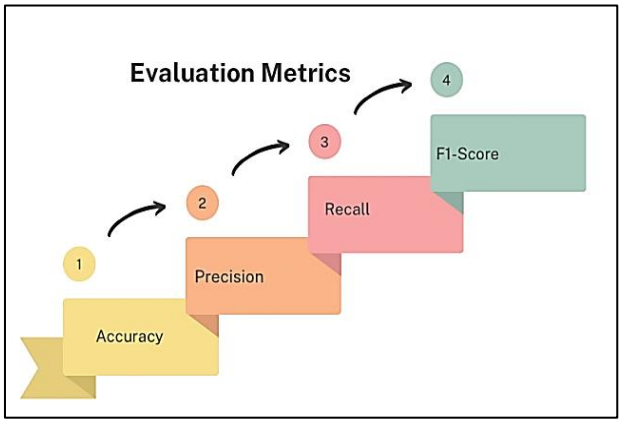

Figure 4. Evaluation Metrics

3.4.1. Accuracy

One of the most common classifications of a model to be used in vulnerability detection is accuracy. It estimates the ratio of correctly forecasted instances, both vulnerable and non-vulnerable, to the overall number of samples. [16,17] Although accuracy will give a speedy view of overall performance, it is misleading in highly skewed datasets, wherein the majority of code snippets may be non-vulnerabilities. There, a score of high accuracy cannot accurately indicate the model's real potential to identify low-probable critical vulnerabilities.

3.4.2. Precision

Precision measures the correctness of positive predictions as a ratio between the number of vulnerable code snippets that were correctly detected and the total number of code snippets deemed to be vulnerable. High precision means that the model creates less false positives, where, in the practical scenario, the use of false alarms can crush the developers, causing them to lose confidence in the automated tool. That is why precision is also a significant measure of the reliability of a model's vulnerability predictions.

3.4.3. Recall

This metric measures the percentage of real vulnerable pieces of code that the model correctly detects. A high recall indicates that the model is very effective at preventing missed vulnerabilities, keeping false negatives reasonably low. Remembering is especially essential in security, where failing to identify a vulnerability may have disastrous results, such as being exploited by malicious actors. However, models with a very high recall may simultaneously lose precision by falsely predicting vulnerabilities.

3.4.4. F1-Score

The F1-score is an equally weighted method of measurement because it combines both precision and recall into a single score, calculated as the simple divisional mean of the two. It also works well with imbalanced datasets and is considered useful in such cases because it takes into account both false positives and false negatives. The higher the F1-score, the better the model tends to do as far as striking the balance between reporting as much vulnerability as possible (recall) and reporting as few false positives as possible (precision) is concerned. This renders the F1-score a more ideal measure of measuring the compliance of vulnerability-detecting systems.

3.5. Proposed ML-Based Vulnerability Detection Framework

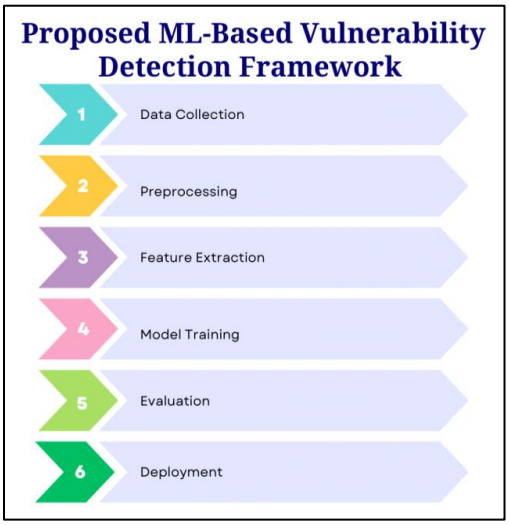

Figure 5. Proposed Ml-Based Vulnerability Detection Framework

3.5.1. Data Collection

The systematic collection of a variety of representative sets of data forms the basis of the proposed framework. [18-20] It utilizes sources like GitHub repositories, Common Vulnerabilities and Exposures (CVE) database, and National Vulnerability Database (NVD) to download both vulnerable and non-vulnerable code snippets. The dataset will cover real-world coding aspects, including vulnerability patterns and programming language diversity, providing a robust foundation for model training.

3.5.2. Preprocessing

Raw code data can be inconsistent due to irrelevant comments, project-specific variable names, and inconsistent formatting. Preprocessing methods like tokenization, AST generation, and normalization help transform unstructured code into structured form for machine learning models and eliminate harmful noise.

3.5.3. Feature Extraction

The code introduces different feature extraction methods to facilitate models in learning relevant patterns. Various methods to capture aspects of code semantics and structure, including Bag of Words (BoW), word embeddings (e.g., Word2Vec, code2vec) and graph-based features based on ASTs or Control Flow Graphs, capture many different aspects of code semantics and structure. Representations ensure the retention of both surface-level and deep semantic information, enabling the training of models.

3.5.4. Model Training

After creating features, several machine learning and deep learning models are fitted to distinguish the vulnerable and non-vulnerable code snippets. Classical models, such as SVM and Random Forest, offer a baseline performance, while newer-generation deep learning models, consisting of CNNs, RNNs, and GNNs, can capture complex patterns in both sequential and

structural data. CodeBERT and other transformer-based models are also trained in a way that makes them better at using contextual associations in large code corpora.

3.5.5. Evaluation

Using standard measures and scores like accuracy, precision, recall, and F1-score to test well-trained models. The reason behind this step is simple: it will not only guarantee that the model performs well overall but also that there exists a balance between the minimum number of vulnerabilities it identifies and the number of false alarms. Cross-modelling assessment helps determine the most promising strategy for practical implementation.

3.5.6. Deployment

Lastly, the most successful model is then incorporated into a deployment pipeline, where it can be used to work on actual software projects. The deployment phase involves integrating the model into developer or CI/CD pipelines to fully automate the detection of vulnerabilities in code under development and during the review process. This guarantees that vulnerabilities are discovered before it is too late to fix, thus lowering the exposure to security breaches.

4. Results and Discussion

4.1. Experimental Setup

The computer-based experiment is used to make a research environment that is both efficient and scalable, and that can handle large datasets and the training of deep learning models that require a lot of computing power. The hardware setup is an experiment includes system installed with NVIDIA GPU, allowing for training and inference of deep learning systems, like CNN or RNN models and transformer-based models, CodeBERT. This is achieved through the 32 GB of system RAM, provides necessary capacity for the preprocessing data, extracting features, and training with large batches without a memory bottleneck. The settings that strikes balance between fast computing and memory size enabling support of complex models and structured representations, such as graphs, including Abstract Syntax Trees (ASTs) and Control Flow Graphs (CFGs). The software part of the implementation is mostly dependent on Python widely supportive of machine learning and data science operations. Python acts as a data and feature preprocessing engine which is allowing the combination of various model structures.

The TensorFlow is a primary deep learning framework, provides excellent support to build, run, and optimize any form of neural network architecture, like CNN, RNN, GNN and transformer-based systems. Scikit-learn is used toimplement classical ML models like Logistic Regression, Support Vector Machines (SVM) and Random Forests for dividing and normalization of the dataset and its evaluation based on metrics such as accuracy, precision, recall and F1-score. The cross-compatibility of TensorFlow and Scikit-learn is sufficient to experiment easily within classical and modern viewpoint. Moreover, the auxiliary libraries are used such as NumPy and Pandas facilitates the efficient numerical computation, structured data manipulation. Matplotlib and other visualization tools are utilized to monitor results and training performance, creating a robust environment for rigorous experiments, aiding both traditional and deep learning methods in identifying vulnerabilities.

4.2. Performance Analysis

Table 1. Model Performance Comparison

Model	Precision	Recall	F1-Score
SVM	0.82	0.78	0.80
Random Forest	0.85	0.81	0.83
CNN	0.88	0.85	0.86
Transformer (CodeBERT)	0.92	0.90	0.91

4.2.1. Support Vector Machine (SVM)

The SVM model had a precision of 0.82, a recall of 0.78, and an F1-score of 0.80. These findings indicate that SVM is quite successful in separating vulnerable and non-vulnerable code snippets, with its recall value suggesting that it does not detect all actual vulnerabilities. Such a constraint arises from the use of more handcrafted features by SVM, i.e., token frequencies or embeddings, which do not necessarily capture the full semantic content of a source code. Nevertheless, SVM offers a good foundation platform that has relatively fewer computational requirements.

4.2.2. Random Forest

The Random Forest model performs better than SVM, with precision, recall, and F1-score values of 0.85, 0.81, and 0.83, respectively. The Random Forest is an ensemble method of learning utilising several decision trees improve noise tolerance and feature diversity. Its enhanced recall indicates the higher capability to acquire vulnerability with minimal growth of false positives.

This trade-off makes Random Forest as a respectable choice compared to more traditional machine learning methods, though it may not able to deal with highly complex and context-sensitive vulnerabilities effectively.

4.2.3. Convolutional Neural Network (CNN)

The CNN model improved performance even more, with a precision of 0.88, a recall of 0.85, and an F1-score of 0.86. CNNs are great at finding local patterns in code token sequences. They can find more subtle vulnerability indicators that are harder to see with regular models. The fact that they automatically extract hierarchical features with little to no manual work. Even though CNNs work well, they have some limits when it comes to modeling long-range dependencies in code. This could mean that they can only be used to find certain types of vulnerabilities.

4.2.4. Transformer (CodeBERT)

The CodeBERT model, a transformer-based approach, achieved the highest precision and recall with a 0.92 precision, 0.90 recall, and 0.91 F1-score, demonstrating its ability to identify syntactic and semantic connections in code. Its self-attention processes make it better at detecting false positives and missed vulnerabilities, making it a promising area for automated vulnerability detection.

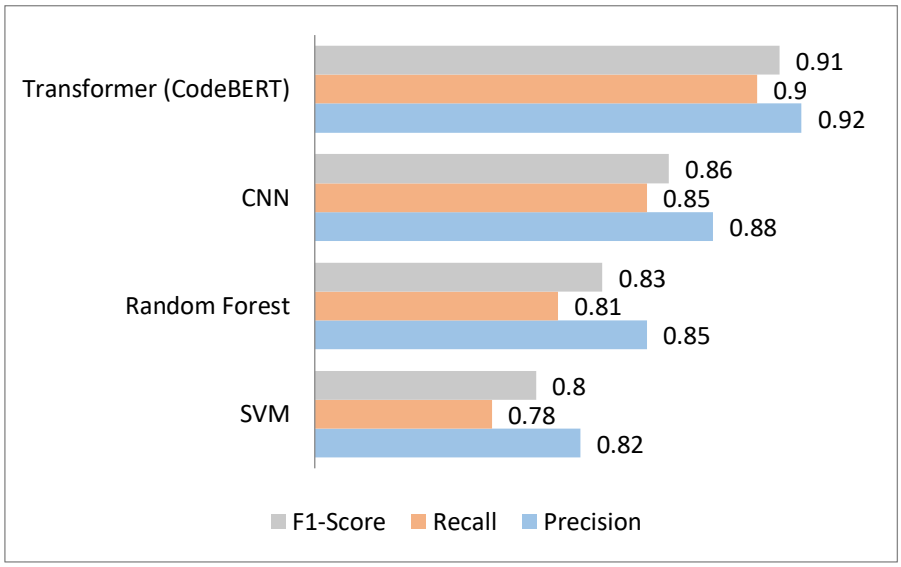

Figure 6. Graph Representing Model Performance Comparison

4.3. Key Findings

The experiment reveals that traditional methods for finding vulnerabilities have flaws. Transformer-based models like CodeBERT show confidence and perform better than traditional machine learning methods like Support Vector Machines and Random Forests. Transformers use self-attention mechanisms to find long-term dependencies and semantic links in the source code, making them better at applying to various types of code and projects. Abstract Syntax Trees (ASTs) embeddings show how software parts are logically and hierarchically connected, providing a more complete picture for detecting bugs. However, dataset imbalance has persisted, making it harder to apply results to other datasets. The study highlights the importance of dataset curation, interpretability, and resilience to adversarial data. The transformer-based CodeBERT model had the highest score, with a precision of 0.92, recall of 0.90, and an F1-score of 0.91. CodeBERT uses self-attention processes to learn long-range interdependencies and context better than CNNs or other traditional models, reducing false positives and missed vulnerabilities. Pushing transformer-based models, which are more computationally complex, seems to be the most promising area of automated vulnerability detection due to their state-of-the-art performance.

4.4. Limitations

The study's promising results highlight limitations in its vulnerability detection framework, particularly in transformer models and advanced deep neural networks, which require significant processing power. CNNs, GNNs, and, in particular, transformer-based architectures like CodeBERT require a considerable amount of hardware resources and can demand high GPU performance and extensive memory capacity. This demand not only makes the experimentation more expensive but also restricts access to the smaller research organizations, groups or developers who do not have access to high-performance computing environments. Moreover, these models may have a relatively long inference time, which can prove to be an obstacle to real-time

vulnerability detection in Continuous Integration/Continuous Deployment (CI/CD) pipelines, where scalability and efficiency are core factors. The second major limitation is that there are no publicly available large-scale datasets of vulnerabilities.

To source data applicable in a supervised framework, although resources such as GitHub, CVE, and NVD are useful for information, they are, however, dissected, unbalanced, and unlabeled enough to be insufficient for training purposes. Most publicly available datasets are either small or skewed towards certain programming languages or types of vulnerabilities; therefore, models generated using these datasets are not easily generalizable to software ecosystems other than those used in training. This lack of good, labeled data severely limits the potential of machine-learning methods because models can easily assume that specific classes of vulnerability (in limited domains) and fail to generalize the vulnerability patterns. Even more, the desire to keep the information to protect organizations and their networks, together with confidentiality and security issues, does not allow most the organizations to publish the real-world vulnerability data, contributing to the matter even further. Although data augmentation and synthetic dataset generation offer a partial solution, they do not provide a complete alternative to the usefulness of large, representative datasets generated by testing on real, vulnerable systems. On the whole, these constraints address two-fold issues related to both computational complexity and the scarcity of data in the domain of ML-based vulnerability detection. To address these issues, we must enhance model architecture efficiency and establish and share standard large-scale vulnerability benchmarks for research and practice.

5. Conclusion

The study reveals that machine learning (ML) methods have significant potential for identifying vulnerabilities in Open-Source Software (OSS), surpassing traditional methods like static analysis tools, dynamic testing, and manual code review due to their ability to automate detection and identify intricate patterns. The deep learning model and transformer-based architecture were the most accurate among the examined models. Conventional and recurrent neural networks have been able to detect sequential and structure-based patterns. Graph-based models, on the other hand, utilise control flow and syntax trees in detecting logic-based vulnerabilities. In particular, encoder-based transformer models, such as CodeBERT, performed best relative to competitors due to their capacity to learn long-range dependencies and semantic interaction spaces in source code by employing the attention mechanism.

Consistent with these results, ML-based methods are not only effective in enhancing detection results but also have high potential for real-world application in large systems of software developers. Although these findings are encouraging, there are opportunities to expand this study to overcome existing bottlenecks in the research and improve its applicability. Another direction of critical importance is the development of large and standardized benchmark datasets, especially customized to OSS vulnerabilities. This diversity of programming languages, project domains and vulnerability types would mean such datasets will make models generalize better. The second significant area refers to the usage of Explainable AI (XAI) methods to enhance the transparency of models and establish trust among developers. Because fully trained deep learning and transformer models are typically run as black boxes, their explainability could facilitate their adoption and debugging (e.g., by allowing developers to see which text is marked as vulnerable and understand the reasons behind the classification). Moreover, federated learning provides an excellent opportunity to cope with the questions related to privacy and data-sharing in the OSS society.

Federated learning can be used to address (a) privacy violations by permitting models to learn with each other over distributed sets of data without exchanging confidential code, and (b) diversity by expanding and augmenting the diversity of the dataset. Lastly, the integration of ML-based vulnerability detection solutions with DevSecOps pipelines will enable real-time, continuous monitoring of software projects. Such integration would help identify and correct vulnerabilities during the development process, thereby reducing the security risks of the systems and the cost of remediation. On the whole, all the identified future research directions focus on the significance of scaling, transparency, and privacy in the development of ML-based vulnerability detection, which will, eventually, lead to more secure and trustworthy OSS ecosystems.

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