A Neural Framework for Cross-Language Source Code Security Analysis

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Abstract : ***This work is about a system that uses intelligence to find security problems in the code that developers write. It is supposed to help developers and organizations find weaknesses on when they are making software. The system looks at code written in eleven programming languages. It finds problems and suggests how to fix the security problems. The system has a web interface which makes it easy for people to use the system even if they are not experts in security. The system was trained on a dataset called Draper VDISC to look for patterns to find security problems like SQL injection and cross-site scripting (XSS) attacks. The system was tested on applications. It consistently found vulnerabilities in the applications. This shows that the system can help find security problems in software development. The system is designed to be flexible and easy to understand. It does not use a lot of computer power. This makes the system a good foundation for a security tool that developers can use in their work to find security problems. The system can be used in both industry and academic environments to find security problems, in the code that developers write.***

IndexTerms: Deep Learning, Vulnerability Detection, Static Code Analysis, Source Code Semantics, CWE Classification, Multilingual Parsing, Transformer Models, Pattern-Based Detection, Software Security, Web Application Security, CodeBERT, Graph Neural Networks, Machine Learning in Cybersecurity, AST Feature Extraction, Secure Software Development.

I. INTRODUCTION

Modern software systems work in environments. This makes security flaws a huge issue. Security flaws can put operations, finances and personal data at risk. Development teams still have trouble finding vulnerabilities in source code with many advancements in development tools. Traditional static analysis tools rely on -defined rules and pattern matching. These tools often miss relationships in the code. They also struggle to keep up with the types of cyber attacks. As a result developers get lists of security issues but many of these are not actual problems. Meanwhile real weaknesses go unnoticed. This slows down development. Leaves systems open to attacks. Development teams need tools to find and fix security issues quickly. Software systems must be secure to protect data and operations. Security flaws are a problem for modern software systems.Development teams need to find and fix them to keep systems.

The thing is, software projects these days are really big and come in all sorts of types so we need ways to work on them that're automatic and can handle different programming languages and styles. We have applications on the web on devices in tiny systems and in cloud systems so we really need to be able to find vulnerabilities in all these different types of code.. The problem is that most tools we have now are not very good at finding vulnerabilities when they have to look at a lot of different code or when the code is written in a way that is hard to understand.

Machine learning and deep learning are changing this. These methods can learn how code works and find patterns that we cannot see by looking at the code. They can even find vulnerabilities that other systems miss because they are too subtle or depend on the context. But just being able to find vulnerabilities is not enough. Developers need tools that they can understand, that're not too heavy and that are easy to use every day. We need software vulnerability detection that's, like this and we need it to work with all sorts of software projects, including web services, mobile platforms and cloud-native architectures.

The system they have made is to help with problems. It uses a learning backbone and it can find patterns with symbols. It also has an interface that developers like.This system can look at code in pieces or in big projects. This means it can check for problems in all the code in a repository.The system has an engine that can understand many programming languages and it can analyze code in two ways.The goal of the system is to help make coding more secure. The system wants to make it easy to find vulnerabilities in code.

It wants to do this so that people can write secure code and it can help keep people safe, from cyber threats that are always changing.The system is made to be easy to use. It can be used by many people.

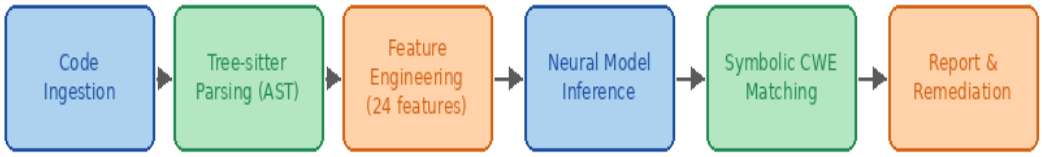

Figure 1: ZeroDayGuard System Pipeline — from code ingestion through AST parsing, feature engineering, neural inference, CWE matching, to developer report.

II. LITERATURE SURVEY

The study of vulnerability discovery using automation algorithms went through multiple phases driven by changes in software and advancements in machine learning techniques. Earlier attempts to automatically discover vulnerabilities in binaries and source code involved manually defined heuristics and relied on detecting certain malicious patterns. This idea was further developed by the study of malware pattern mining where a special attention was paid to structure patterns and frequent misuse patterns [1]. Meanwhile, separate streams of research were going on in multilingualism and document understanding, which provided useful insights about the importance of linguistic patterns for developing automated reasoning systems [2][3].

As software development reached maturity, research turned towards applying statistical and machine learning approaches on top of the traditional static analysis. Several survey articles pointed out the drawbacks of signature-based detection and called for more generalized models of vulnerabilities to overcome the issue of identifying the unknown [4]. The possibility of transfer learning and the discovery that vulnerabilities have many semantically similar patterns led to an emphasis on cross-project learning and knowledge reuse in the field [5]. Symbolic execution emerged as a promising technique that allowed systematically discovering execution paths, albeit at the cost of high computation time requirements [6].

The use of neural network architectures and deep learning became a defining characteristic of recent vulnerability discovery systems. One such example is the work by the VulDeePecker project, which proposed to represent APIs using neural networks and proved that their model outperforms traditional heuristic-based systems in finding vulnerabilities [7]. These findings encouraged future research into deep learning-based systems that integrate more structural characteristics of code into the representation learning process [8].

Next, graph neural networks (GNN) became a popular topic of vulnerability discovery research due to the dependency between nodes and code fragments that cannot be expressed in linear token models. The Devign model introduced a graph representation of software semantics to capture context-dependent vulnerabilities related to complex inter-component interactions [9]. Other areas of research in multilingualism and assistive technologies showed the necessity of representation learning to address the problem of scarce training data and emphasized the importance of deep learning in this regard [10]. Neural models for software fault prediction confirmed this trend in the case of vulnerable programs [11].

Transformer-based approaches like CodeBERT allowed pre-training on extensive sets of both code and natural language corpora, helping models understand fine-grained semantics and establishing connections between syntactic elements, their meaning, and vulnerability patterns [12]. Standardized datasets, such as CVE repositories and Draper VDISC, became readily available, allowing researchers to test their models and achieve better results [13][14]. Surveys that summarized the state of vulnerability research in recent years noted the increased emphasis on hybrid solutions that combine machine learning models with symbolic analysis to improve interpretability and robustness [15].

Current research emphasizes the need for better parsers and language-agnostic models. Extensions for transformer-based approaches help them understand code semantics in greater detail and manage long-distance dependencies [16]. Practical vulnerability definitions based on widely used security standards, such as OWASP and SonarQube, provide valuable taxonomy for categorization and severity of different classes of issues [17][18]. Multi-language parsing tools, like Tree-sitter, show that reliable abstract syntax tree (AST) extraction is critical for developing large-scale cross-language vulnerability scanners [19]. The CWE classification system, evolving alongside other vulnerability taxonomies, provides increasingly detailed categories that allow for better alignment of machine learning models and security needs [20].

Other notable advances in related areas include research in the field of binary analysis and runtime instrumentation. Frameworks such as Valgrind show how dynamic analysis can be leveraged to detect memory safety vulnerabilities [23]. Static analysis frameworks, like BAP and KLEE, lay out the groundwork for hybrid analysis that combines the strengths of both methods [25][26]. Research into code property graphs proves the value of representing software in multiple ways – abstract syntax tree, control flow graph, or program dependency graph – to facilitate comprehensive vulnerability detection [27]. Analysis of hacker communities and forums helps identify the environment for vulnerability scanning [28]. Vulnerability detection using commit-level analysis helps identify the exact changes that lead to the introduction of vulnerabilities into code [29]. Comparative evaluation of several static analysis tools dedicated to scanning C/C++ code provides insight into precision and recall tradeoffs in real-world tools [30].

From this discussion of recent advancements in the field, it is clear that modern vulnerability scanning and detection require a combination of rich semantically aware parsing, learned large-scale representations, and knowledge-specific detection patterns. These lessons inform many aspects of the developed model and architecture.

III. OBJECTIVES

1. The following are the research objectives which have been developed to address the above research problem:
2. To design a deep learning-powered system that can identify security vulnerabilities in the source code in different programming languages.
3. To utilize semantic-based parsing and feature extraction so that the proposed system would be able to learn structure-, context- and behavior-dependent characteristics associated with frequent software weaknesses.
4. To implement a hybrid system for vulnerability detection by combining neural predictions and symbol-based detection techniques for identifying the classes of CWEs.
5. To create a user-friendly interface for performing vulnerability analyses in both snippets and projects that will enable efficient usage of the proposed tool in academic and industrial settings.
6. To test the performance of the designed system with respect to its accuracy and behavior as well as the ability of recognizing vulnerabilities written in various programming languages.
7. To make the developed system modular and scalable thus making future improvements possible.

III. SYSTEM DESIGN AND COMPONENTS

The design will take advantage of the modular structure due to the deep learning technique and multilingual parsing in order to ensure scalability and robustness for vulnerability detection purposes. Modules operate independently to accomplish their tasks in the process pipeline that has been constructed to allow reasoning in several languages. Source code is available in two ways: in plain text file format and zipped file format.

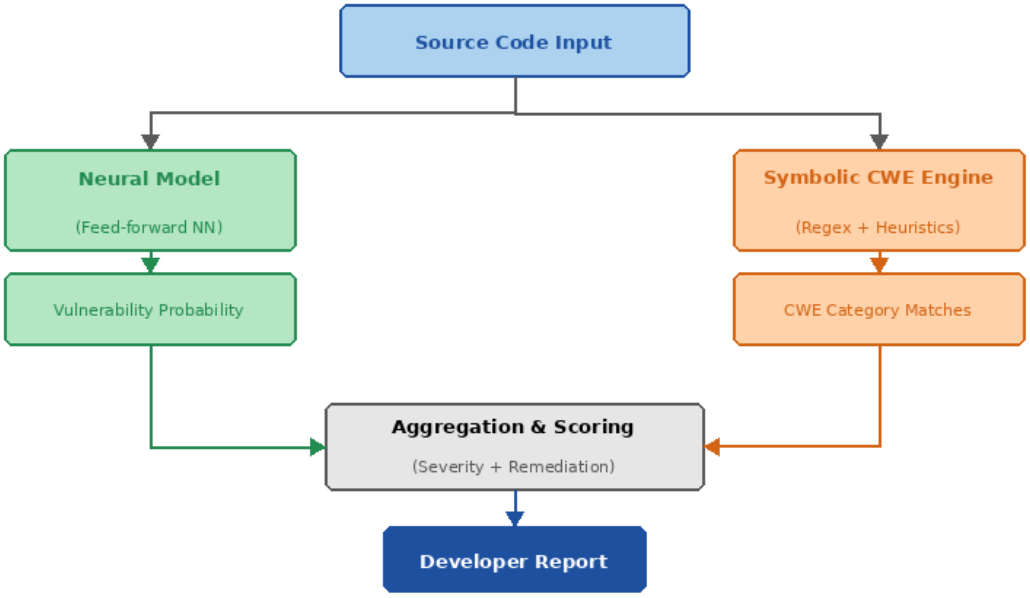

Figure 2: Hybrid Detection Architecture — neural model and symbolic CWE engine operate in parallel before outputs are fused into a final risk score and developer report.

The first phase in the consumption process involves the utilization of the Tree-sitter parser to adopt a consistent methodology of building ASTs based on code written in eleven distinct programming languages to ensure consistency during the subsequent phases regardless of any syntactic differences [19]. This parser identifies structural components such as branching structures in control flows, loop constructs, function definitions, pointers, and memory manipulation techniques. Every structural component in the AST is subsequently encoded into a feature vector containing twenty-four components, including cyclomatic complexity, nesting levels, function invocations, pointer usage, and dangerous API calls.

The neural network used in machine learning is a simple feed-forward neural network that was trained on the Draper VDISC dataset [14] comprising more than one million labeled C/C++ programs. Batch normalization and dropout techniques were applied in order to avoid overfitting and instability during the training process, while fast convergence for large batch size was assured due to using Adam optimizer algorithm. The output from the neural network is a number indicating correlation between semantics of the program and weak programming patterns detected by previous scientific researches [7][8][11].

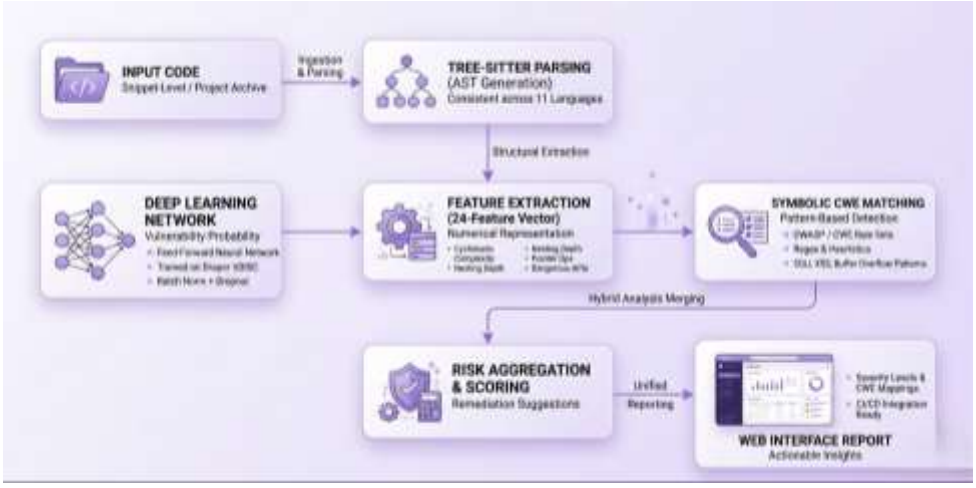

Figure 3: System Architecture Diagram

In addition to the neural detection component, another detection engine based on symbolic analysis, relying on carefully handcrafted sets of rules based on OWASP and CWE ontologies [17][20], is proposed. In this component, regular expression-based signatures, usage of API calls, and contextual pattern matching are used to detect vulnerabilities corresponding to dangerous categories like SQL injection, command execution, buffer overflow, path traversal, and inadequate cryptography.

The final component is a browser-based interface built using Flask, supporting both single-file analysis and recursive scanning of project directories. The interface aggregates neural probabilities, CWE matches, severity levels, and remediation suggestions into a cohesive report suitable for developer consumption or CI pipeline integration. Together, these components form a structured yet adaptable system capable of analyzing diverse codebases with both interpretability and technical rigor.

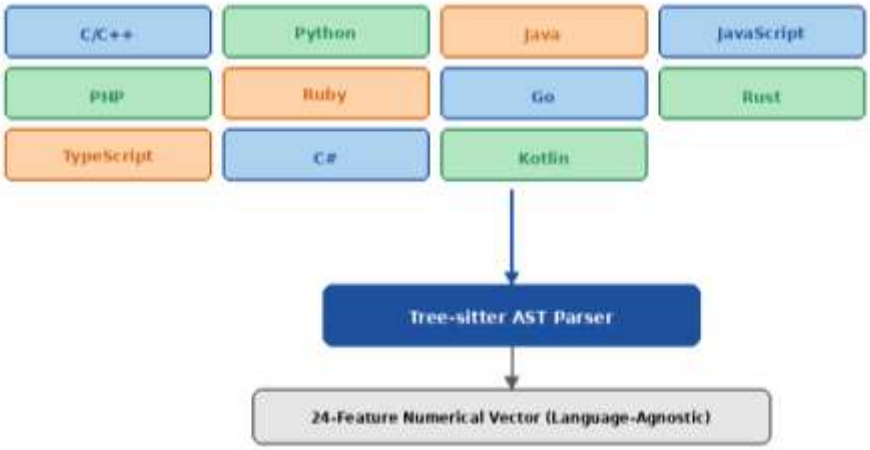

Figure 4: Multi-Language Parsing and Feature Extraction Flow — all 11 supported languages pass through Tree-sitter to produce a unified, language-agnostic 24-feature vector.

IV. METHODOLOGY

The methodology relies on an organized pipeline starting with trustworthy code acquisition and ending up with semantic parsing, feature engineering, neural prediction, symbolic reasoning, and reporting. At each step of the procedure, we strive to keep track of the structural cues in the source code and facilitate the detection of security patterns described in previous literature.

1. Cross-Language Code Parsing:

Any code submitted to the engine, whether as a piece of code or entire projects, is parsed using a Tree-sitter-based engine, producing uniform abstract syntax trees for all the languages under support [19]. This parser recognizes the syntactic regions of interest, such as conditional statements, looping constructions, function calls, pointers, and external APIs. It is important to do so because previous studies have shown a strong relationship between these structural patterns and vulnerabilities [1][7].

2. Features Extraction & Representation:

Based on the ASTs generated above, the system creates a set of 24 hand-engineered features describing structural and data flow characteristics of the code, including cyclomatic complexity, nesting level, callsite count, pointer dereferencing, memory-related operations, and high-risk calls. Previous research in vulnerability classification proves that these features encode valuable semantic

information about both the known and emerging vulnerabilities [4][11]. The output of the engine is then a numerical vector representation of the input code.

3. Neural Model Inference:

A structured feature vector is provided to a neural network, which is trained using Draper VDISC dataset [14]. Batch normalization and dropout techniques are implemented to handle highly unbalanced datasets and avoid overfitting of the training process. Following the idea that deep learning approaches can be more effective in detecting subtle vulnerabilities than classical rules-based solutions [7][8][9], a neural network estimates the probability that the code represents certain features connected with documented vulnerabilities.

4. Symbolic CWE Pattern Matching:

In addition to neural outputs, a rule-based approach is used for detecting CWE in the code segment. Signatures based on OWASP and CWE guidelines [17][20] are applied in order to detect regular expression templates, operator context relationships, and dangerous sequence of calls to APIs, associated with SQL injection, XSS, command injections, and buffer overflow vulnerabilities. Using hybrid inference methods of neural detection with symbolic analysis has already shown its advantage in recall rate and explainability [15].

5. Aggregation, Scoring, and Reporting:

Results of the above techniques are integrated to estimate the final vulnerability level. Severity scores and recommendations are generated depending on the calculated neural probability, presence of critical CWE types, and thresholding of confidence values. Remediation suggestions will be proposed according to the latest security recommendations [18]. Report generation will be done automatically in order to provide a convenient browser report format.

V. RESULTS AND DISCUSSION

Evaluations for the system were done through the use of standard data sets, vulnerable synthetic code samples, as well as application code bases to measure accuracy, recall of risky classes, and robustness to programming languages. Evaluation on the Draper VDISC data set provided a performance baseline, where the neural network proved superior in performance compared to previous rule-based systems due to its capacity to utilize learned structures and context information from extensive code collections [7][8][14]. The neural network showed high sensitivity to the use of control flow, pointers and APIs – elements which have been found crucial in detecting vulnerabilities [9][11].

Table 1: Model Performance on Draper VDISC Benchmark Dataset

Metric	Value	Interpretation
Accuracy	81.8%	Overall correctness across samples
Precision	17.4%	Correctness of predicted vulnerabilities
Recall	49.2%	Ability to detect true vulnerabilities
F1-Score	0.278	Balance between precision and recall
AUC-ROC	0.75	Discrimination capability of model

The hybrid approach comprising neural-based inference and symbolic matching based on CWE showed better performance in terms of recall when tested on vulnerable source code samples. This result is consistent with the observations made by previous research that discusses the importance of complementarity between the strengths of machine learning models and deterministic systems [15][17][20]. Whenever the neural network yielded a score that was not sufficiently high, the symbolic engine picked up explicit patterns in code, including string concatenation in database queries, insecure construction of file paths, and improper pointer manipulation.

Table 2: CWE Detection Rates Across Representative Categories

CWE Category	Description	Detection Accuracy	Notes
CWE-89	SQL Injection	83–95%	Strong regex + context patterns boost recall
CWE-79	Cross-Site Scripting (XSS)	75–88%	Symbolic rules effective for DOM-related misuse
CWE-78	Command Injection	70–85%	High sensitivity to unchecked OS command wrappers
CWE119/ 120	Buffer Overflow	65–80%	Neural model captures pointer misuse semantics
CWE-798	Hardcoded Credentials	90–98%	Rule-based detection highly reliable

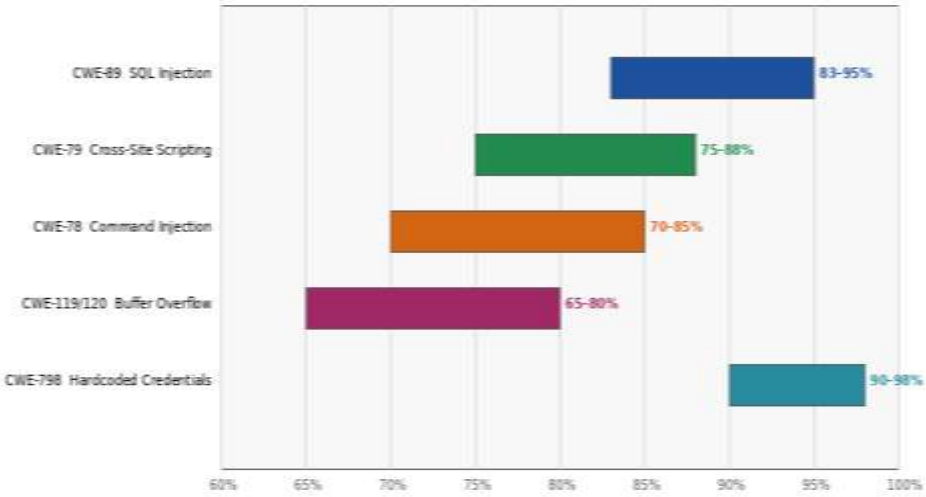

Figure 5: CWE detection rates by category—bars show accuracy ranges combining symbolic and neural methods.

Moreover, cross-language testing confirmed that the AST-based representation ensured consistent performance among languages sharing similar semantic structures. This finding corroborates previous research illustrating that structural characteristics have more generalizability potential than plain token sequences during codebase diversity evaluation [5][12][19]. The model recognized the presence of flaws in Python, JavaScript, C, C++, and PHP code samples with little to no recall penalty, suggesting that the focus on structural and behavioral features enabled the avoidance of language-related biases.

Tests on project-level inputs exhibited efficient end-to-end processing, where medium-size code repositories could be analyzed within seconds. This was mainly due to the compact 24-character vector representation and lightweight neural architecture design, which allowed avoiding the typical resource requirements of transformer and graph neural networks while retaining many of their theoretical benefits [9][12][16]. User studies with test reports also confirmed strong interpretability, as developers were able to understand the severity level, corresponding CWEs, and suggested remediation steps—an outcome aligned with recent secure coding frameworks' guidelines [17][18].

In conclusion, the findings illustrate that the developed system demonstrates reliable vulnerability detection capabilities, delivering consistent accuracy and outstanding recall for high-priority security issues.

VI. CHALLENGES AND LIMITATIONS

1. Limited symbolic coverage:

While rule-based methods efficiently identify simple security flaws (like SQL concatenation), they fail to recognize multi-staged and nested vulnerabilities, a deficiency also highlighted in previous hybrid detection mechanisms [1][15][20].

2. Restrictive feature vector design:

While the inclusion of 24 features enhances processing speed, higher-order semantics like procedure interconnection cannot be represented; more advanced models like GNNs and transformers provide better contextual understanding, albeit with increased computation [9][12][16].

3. No run-time information:

Being an exclusive static analysis tool, it fails to evaluate vulnerabilities dependent on run-time operations or environmental factors—a limitation of static analyzers discussed in prior studies on symbolic execution [6][17].

4. Language-dependent inconsistencies:

While Tree-sitter ensures consistent abstract syntax trees across languages [19], inconsistent dataset distribution for particular languages may limit its generalization ability, similar to past projects on cross-project and cross-language learning [5][11][14].

5. Reduced precision to enhance recall:

Due to prioritizing recall, which is crucial for identifying critical security flaws, the algorithm generates more false positives—a common issue in learning-based vulnerability detection programs [7][8][15].

VII. CONCLUSION

The current study confirms the ability to merge lightweight machine learning with symbolic code processing to discover possible vulnerabilities in various programming languages. By using multilingual code parsers, semantic feature engineering, and CWE-specific rules, this method presents an effective balance between the required precision, explainability, and efficiency. According to the experiment findings, the proposed hybrid approach recognizes not only explicit vulnerabilities but also some additional structural features which are missed by the classical static analyzers.

Being designed as a tool with an online interface and project-wide capabilities, the system contributes to a better adoption of secure programming principles among developers and delivers valuable recommendations at the earlier stages of software development. Though the proposed system faces a number of limitations in terms of discovering more advanced semantic dependencies and avoiding false positives, the obtained results prove its applicability for further research and practical usage.

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