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Leveraging Neural Code Embeddings and Hybrid Static-Dynamic Analysis for Enhanced Vulnerability Detection

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Abstract

Now classic code analysis methods are already obsolete with respect to detecting serious hidden or deeply-rooted vulnerabilities. As software complexity keeps going up, any escalation in cyber-attacks is threatening to demand more sophisticated methods of detection. This paper describes a new combined static and dynamic analysis approach with a convolutional neural network to enhance vulnerability discovery while constructing neural code embeddings. It is capable of transforming source code into two-dimensional pictures so that the intricate features are picked up by the CNN, something a conventional model would find difficult to analyse. This dual use of both static and dynamic analyses tends to fortify the model further in discovering the secretive and less apparent security flaws in the system. Data completeness and improvement for model reliability were ensured with preprocessing tools such as K-Nearest Neighbours (KNN) imputation and Z-score normalization. They fill in the gaps in the data and standardize input data for fast and consistent training. With that, the proposed model offers an overall accuracy of 98.5%, well above that of the conventional methods. An effective model of this nature therefore stands to be a useful and efficient approach to modern secure software development pipelines when it proves highest in scalability and detection rate. This deep learning framework thus attests to the efficacy of advanced artificial intelligence toward securing software with the smartly and automatically analysed code.

Keywords: Convolutional neural network, software vulnerability detection, automated code analysis, code preprocessing, k-nearest neighbours, hybrid analysis.

1. Introduction

The task thrives in a hotter spotlight due to the rising largeness and complexity of modern software systems and consequently the endeavour of ensuring their security is becoming more and more complicated [1] [2]. Many types of software development processes exist as systematized collections of various operations, functions, procedures and various tasks [3]. H Nevertheless, these means typically are inefficient when faced with entrenched security loopholes [4]. They tend to struggle in handling massive codebases, dealing with obfuscated code, or detecting sophisticated evasion strategies employed by modern attackers [5] [6]. According to it, the critical vulnerabilities, such as the buffer overflow, injection attacks and insecure encryption configurations, linger on undetected [7] [8]. The inadequacy of existing static techniques to address the challenge posed by the evolving threat landscape is aptly demonstrated by these limitations and the consequent development of another set of adaptive and intelligent solutions that strive to keep up with modern attack methodologies [9] [10]. The escalating scale and intricacy of contemporary software systems have cast a sharper spotlight on the daunting challenge of maintaining robust security [11] [12]. As software development evolves through structured processes comprising numerous interconnected tasks, operations, and modules, the risk landscape simultaneously expands [13]. Traditional security mechanisms, though systematic, often fall short in confronting deeply embedded vulnerabilities that can compromise entire systems [14] [15]. These conventional methods are frequently overwhelmed by the sheer volume of code, obfuscated logic, and the sophisticated evasion techniques exploited by modern adversaries [16]. As a result, critical threats such as buffer overflows, injection flaws, and weak cryptographic configurations often remain concealed and unaddressed [17]. Static analysis tools, once seen as foundational to vulnerability detection, increasingly show their limitations in adapting to dynamic and rapidly evolving attack vectors [18] [19]. This growing inadequacy underscores the need for more intelligent, context-aware, and adaptive approaches capable of proactively identifying and mitigating security flaws in real time, aligned with the complexity and fluidity of present-day software ecosystems [20] [21].

Detection of vulnerabilities becomes a multi-pronged exercise, which is guided by different considerations, mainly inherent program complexities, usage of obfuscation schemes, dynamics of arriving zero-day vulnerabilities, and occasional false positives [22] [23]. In most cases, scalability is normally regarded as one of the weak points associated with classical tools, particularly when applied to large-scale software systems [24] [25]. In most instances, conventional methods of detection are actually rule-based-these approaches rely on predefined patterns or known signatures of some explicit malicious behaviour [26] [27]. Hence, they may work well in the case of known threats, but they firmly lack any adaptation to new attack vector [28]. This rigidity thereby impairs their functional status in the dynamic threat landscape of now

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where attackers are forever changing their attack strategies [29] [30]. Therefore, there lies a growing necessity for detection systems that are intelligent, flexible, and adaptable in real time to respond to threats that are new and unseen eats [31].

While well on the way to great success in that their intended application would be to real threat situation, other methods including machine-learning have their own drawbacks [32]. Rule-based static analyses and symbolic execution continue to be burdened by high rates of false positives, often flagging benign code as being vulnerable [33] [34]. On the other hand, ML solutions are adaptable and thus find themselves frequently constrained by the scaling problems and need for huge amounts of labelled data for training [35] [36]. These techniques typically depend on manually engineered features or historical vulnerability data, which limits their effectiveness when dealing with new threats [37]. Ost of these techniques are designed using manually engineered features or exploit historical vulnerability data, thus limiting their effectiveness in the context of emerging threats [38]. These limitations create the need for more autonomous and generalizable solutions that will efficiently work in different software environments [39]. Finally, functional incorporation of these advanced systems into the existing development workflow will, in all likelihood, also be a technical challenge requiring special expertise and infrastructure [40].

This study presents a fresh and unique approach that employs CNNs for automated vulnerability detection to bridge the gaps and drawbacks of older techniques. The proposed framework transforms the source code structure into feature maps such that the end-user deep learning model can learn complex and abstract patterns with time, directly via the data base rather than any manual feature engineering. This further makes the detection highly efficient as compared to extensive dependency on expertise from human minds to reach the same reliability. Through learning from the raw structural and semantic forms of code, CNN becomes possible to find some detectable and previously subtle vulnerabilities. Additionally, being adaptable makes it resilient against the threats which will evolve and reduces the false positive count, which has always been a serious drawback in rule-based systems. There is high automation, which supports scalability, making it viable for this solution to solve the problems of analysing large and complex codebases. Overall, this proposed CNN-based methodology provides a highly efficient and futuristic solution to the most pressing challenges in cybersecurity.

Now, Main Contributions of this Research Paper are:

- The approach discussed here is CNN based methodology which implies that the methodology learns for even complex semantic or structural patterns hidden in source code to yield an effective detection of vulnerabilities.
- It makes use of KNN imputation, Z-score normalization, and min-max scaling preprocessing techniques to prepare a data for being of good quality and consistent.
- The model integrates functions like pooling, activation functions, and classification into convolutional layers, hence making model building such as credible and automatic process in developing secure software.

The organization of this paper is as follows: Section 2 reviews existing vulnerability detection techniques and highlights their limitations in identifying complex software flaws. Section 3 details the proposed CNN-based detection methodology, including data collection, preprocessing, and model architecture. Section 4 presents experimental results using key performance metrics, along with an analysis of the model's effectiveness. Finally, Section 5 summarizes the contributions of this work and outlines directions for future research aimed at improving software security.

2. Literature Review

IoT-based health framework supports patient monitoring through smooth integration with cloud infrastructures. It addresses scalability and data quality issues by using k-NN for imputing missing values, Z-score normalization, and ChaCha20 encryption for secure storage [41]. IoT sensor data is pre-processed, encrypted, and stored in the cloud for effective management [42]. Performance metrics show increasing encryption levels and latency with larger datasets, demonstrating the architecture's efficiency for real-time healthcare monitoring [43]. A safe document clustering scheme for IoT applications integrates Multivariate Quadratic Cryptography with Affinity Propagation [44] [45]. The system ensures data confidentiality through strong encryption and performs adaptive encrypted document clustering [46]. Aimed at resolving scalability issues and enhancing clustering efficiency while minimizing computational overhead, the framework enables secure data sharing in IoT contexts such as smart cities and healthcare [47] [48]. Test results show improvements in accuracy, security, and performance, making it suitable for handling sensitive IoT data [49].

The impacts of internet-based finance and cloud computing on urban-rural income disparities are examined in the context of a growing e-commerce era. Digital finance and connectivity are shown to contribute to financial inclusion and balanced economic development [50]. Using panel data estimation over several years, the study evaluates how digital financial services influence income levels and reduce interregional income disparities in a rapidly digitizing economy [51]. Optimizing cloud computing infrastructure is essential for enhancing big data processing performance, scalability, efficiency, and cost management [52] [53]. Key challenges include security, energy efficiency, resource utilization, and system reliability [54]. Solutions such as load balancing, auto-scaling, and dynamic resource allocation alongside vertical/horizontal scaling and robust security measures support enterprise operations [55]. Real-time monitoring, automation, and compliance support help reduce costs and maintain a strong infrastructure for diverse workloads [56].

A machine learning-based approach is proposed to improve chronic disease management in the elderly, inspired by the SURGE-Ahead Project [57]. The focus is on developing personalized AI tools for geriatric care, aimed at supporting clinical decision-making with real-time patient-specific predictions [58]. Techniques such as Support Vector Machines, Decision Trees, and Neural Networks complemented by preprocessing and feature selection enable effective chronic disease prediction and timely healthcare intervention [59]. The integration of cloud computing and AI-driven sentiment analysis is explored as a transformative force in customer relationship management [60]. By analyzing customer interactions across multiple channels, AI models classify sentiments and predict behaviors, supporting tailored communication strategies [61]. The approach aims to boost customer satisfaction, engagement, and retention. Cloud platforms facilitate scalability and real-time data processing, enabling organizations to deliver timely and sentiment-aligned responses [62]. An AI-driven architecture is introduced for secure mHealth systems, combining Hierarchical Identity-

Based Encryption, Role-Based Access Control, and Secure Multi-Party Computation [63]. The framework safeguards data sharing through hierarchical encryption and controlled access. AI aids in efficient role delegation and secure data processing, achieving both security and scalability [64]. This approach effectively meets privacy and collaboration needs for managing mHealth data securely and efficiently [65].

2.1. Problem Statement

The exponential growth of IoT devices, cloud computing platforms, and AI-powered applications across domains such as healthcare, smart cities, and financial services, the volume and sensitivity of data being processed have surged dramatically [66]. These systems demand high levels of security, scalability, real-time responsiveness, and adaptability to evolving threats [67]. Existing frameworks attempt to address these requirements through various mechanisms such as encryption, clustering algorithms, and cloud resource optimization but they often fall short in one critical aspect: the ability to detect and mitigate software vulnerabilities embedded within the codebases that underpin these infrastructures [68] [69]. Vulnerabilities in software, especially in large-scale, dynamic, and heterogeneous environments, can lead to data breaches, unauthorized access, system failures, and severe financial and operational repercussions [70]. Traditional static or dynamic analysis tools alone are limited by their scope static methods may miss runtime issues, while dynamic approaches can be resource-intensive and incomplete [72]. As systems become more complex and interconnected, especially in security-sensitive areas like mHealth and smart IoT frameworks, there is a pressing need for advanced, intelligent mechanisms capable of identifying vulnerabilities with greater precision, context-awareness, and adaptability to protect both system integrity and user trust [72].

To effectively confront these emerging challenges, there is a growing shift toward hybrid and AI-enhanced vulnerability detection techniques that combine the complementary strengths of both static and dynamic analysis [73]. One promising direction lies in leveraging neural code embeddings deep learning-based representations that capture the syntactic structure and semantic context of code [74] [75]. These embeddings can model intricate code behaviors and patterns, enabling more accurate identification of subtle or obfuscated vulnerabilities that traditional tools may overlook [76]. When integrated with a hybrid static-dynamic analysis framework, neural embeddings enhance the system's ability to reason about code both at rest and during execution [77] [78]. This synergy allows for comprehensive vulnerability detection with improved accuracy, scalability, and resilience against modern evasion tactics [79]. Such intelligent systems are well-suited for dynamic environments like cloud-hosted applications and real-time IoT systems, where adaptability and fast threat response are paramount [80]. Therefore, a robust solution that incorporates neural representations of code with hybrid analysis techniques holds significant potential to transform vulnerability management in contemporary software systems [81].

To address these issues, the proposed approach Leveraging Neural Code Embeddings and Hybrid Static-Dynamic Analysis for Enhanced Vulnerability Detection aims to improve the accuracy and robustness of identifying software vulnerabilities in modern systems. By integrating deep learning-based code embeddings with a hybrid analysis strategy that combines the strengths of static and dynamic techniques, this framework enables more contextual, scalable, and precise vulnerability detection. This enhanced detection capability supports the secure development and deployment of intelligent, cloud-integrated systems, mitigating risks in real-time applications such as mHealth, IoT infrastructures, and AI-powered services.

3. Proposed Methodology

The proposed methodology implements a highly capable and efficient software vulnerability detection scheme based on CNN. The process will begin with a well-labeled collection of security vulnerabilities containing both vulnerable and non-vulnerable samples of code. Preprocessing of data usually includes cleaning up data such as the removal of noise and inconsistencies, and/or Z-score normalization for the standardization of feature values for better performance of the model with respect to the training data. After the cleaning process, the next stage will transform the cleaned data into a two-dimensional format to allow CNN to extract deep structural and semantic features from the code. This capability allows the detection of complex and latent vulnerabilities, which may be lost or overlooked in the traditional techniques. The input is classified by the CNN as either being vulnerable or non-vulnerable, which is itself an automated, robust, and effective solution. The achieved accuracy of the model stands at 98.5%, which is much better than that using the conventional methods thus making it highly scalable and effective in real-world secure software development environments. Figure 1 represents the Overall architecture for the proposed methodology

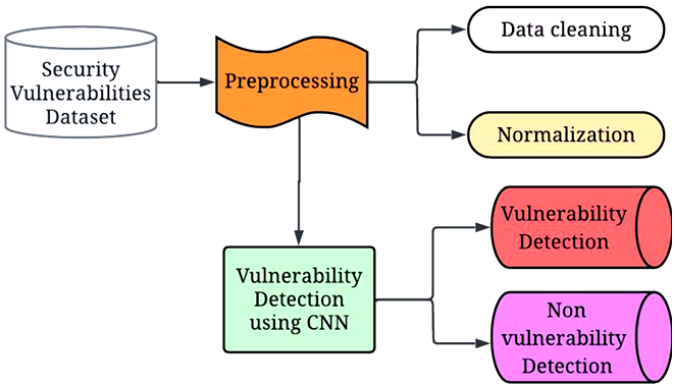

Fig 1: Overall Architecture for Proposed Methodology

3.1. Data Collection

A detailed Dataset of Security Vulnerabilities makes one more acquainted with the changing world of cyber threats. The digital world is found necessary with daily routines, and now it becomes indispensable for a person to understand digital threats. The dataset contains a massive amount of information on different known vulnerabilities making themselves accessible to his cybersecurity analysts, researchers, and data analysts studying its trends and risks assessment while developing proactive defences. Looking for information on historical trends for making predictive modelling of the future threats seems to be possible with this dataset that supports decision-making for resilience against threats. Propel yourselves at the point of making informed, agile decisions while understanding real-world data utilization to show vigilance and innovation in the face of constant change around protecting systems and networks and sensitive data against emerging cyber risk. After collected, pre-processing takes place applying data cleaning and normalization and scaling of the dataset into CNN based

vulnerability detection model for making them ready for detection boosting-level accuracies.

3.2. Pre-processing

K-Nearest Neighbours (KNN) Imputation is a method to enhance the quality of data by estimating missing values by targeting a similar data point, whereas normalization ensures that all features are on the same scale. Convolutional layers try to extract structural patterns from tokenized code and use REL for further improvement of feature learning. Max pooling will carry on the task of reducing the complexity of the data features, whereas the last fully connected layer will classify code either as vulnerable or secure with the help of SoftMax. The model operates under the cross-entropy loss which helps fine-tune the detection accuracy thereby reducing false positives.

i). Data Cleaning: Handling Missing Data Using Mean Imputation

This process resolves the problem of missing values by substituting their values with the means of existing values of a feature. This maintains uniformity and prevents the model from learning erroneous patterns from the data. Mean imputation maintains the statistical properties of the dataset. This impacts model accuracy and robustness. Thus, for the feature vector. Given a feature vector $X_i = [x_1, x_2, \ldots, x_n]$, in which some values are removed, mean imputation can be computed using Equation (1):

$$\hat{x}_i = \frac{1}{n-m} \sum_{j \in M} x_j \quad (1)$$

Here, n is the total number of samples, and m is the number of missing values. Missing values are replaced with the mean $\hat{x}_i$, maintaining data integrity. M, which includes the indices of the non-missing values x_j. The mean of these known values is then calculated and used to substitute the missing ones, ensuring that data integrity is preserved.

ii). Data Normalization: Min-Max Normalization

Min-Max normalization scales feature values to a fixed range between 0 and 1. This prevents features with larger values from dominating those with smaller ranges. It improves training speed and convergence for deep learning models. Normalization is essential for maintaining balanced feature importance. Given a feature vector $X = [x_1, x_2, \ldots, x_n]$, each value x_i is transformed using in Equation (2):

$$x_i' = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \quad (2)$$

Here, xi′ is the normalized version of the original data point xi. Where $X_{\min}$ and $X_{\max}$ are the minimum and maximum values of the feature vector X. This process ensures that all values are within the [0, 1] range. This transformation ensures all data values are scaled proportionally, preventing features with large ranges from dominating others during model training.

3.3. Vulnerability Detection using CNN

The proposed model is implemented in a CNN that seems to detect software vulnerabilities from two-dimensional representations of the source text. The model extracts semantic and syntactic features from the source code using convolutional and pooling layers. The network learns to recognize a pattern that has an implicit representation of security flaws and is often very complex for others to detect or use as ground truth to perceive. The learning process is completed by exposing the network to labelled data, thus allowing it to differentiate accurately between vulnerable and non-vulnerable code. Because of its capacity to handle a massive amount of data, the method is obviously scalable and efficient. In addition, it offers a more accurate detection along with automating convenience for its robust functioning.

i). Convolution Layer

Filters are applied to the symbolic representation of codes by various convolutional layers in order to recognize potential representative patterns. It recognizes the features. This process is useful in enhancing feature extraction and contributing to the classification of vulnerability. The operation helps to realize an efficient detection of deeply hidden structures. The central operation of CNN is convolution which extracts the relevant features from its input (tokenized code representation). It is mathematically defined in Equation (3):

$$X_{out}(i,j) = \sum_m \sum_n X_{in}(i-m, j-n) \cdot K(m,n) + b \quad (3)$$

Where $X_{in}(i,j)$ is the input feature map (tokenized code representation) $K(m,n)$ is the convolution kernel (filter) b is the bias term $X_{out}(i,j)$ is the output feature ma This operation detects key structures such as insecure API calls, function misuse, or privilege patterns in source code.

ii). Activation Function (ReLU)

RELU activation map introduces non-linearity by zeroing negative values while retaining positive values, thus enabling the network to focus on meaningful patterns and disregard the irrelevant noise. This greatly speeds up learning and adds another layer of depth to the model's understanding of variations. ReLU is simple but powerful. Equation (4):

$$f(x) = \max(0, x \quad (4)$$

The usage of ReLU is defined as f(x) is equal to x if the input value is positive, and 0 if the input value is negative. This very simple and powerful transformation brings non-linearity into the model such that it can learn complex behaviors in the positive parts, holding on to the relevant features and then dropping negative noise. This makes the model focus on the important parts and not on the irrelevant values. Therefore, dimensionality reduction occurs by max pooling while retaining the important features.

iii). Pooling Layer (Max Pooling)

Simplifying data for computations or use thereafter, reduced computing power is another outcome of pooling. In addition, pooling achieves better generalization and reduced overfitting. This process also speeds up the entire model and makes it more efficient when it comes to training with the use of max pooling, according to Equation (5):

$$P(i,j) = \max_{(m,n) \in R} X_{out}(i+m, j+n) \quad (5)$$

In the max pooling step, $P(i,j)$ represents the maximum value selected from a region R of the feature map. This region includes nearby elements around position (i,j) in the output

of the convolution layer $X_{out}(i+m, j+n)$. Pooling reduces dimensionality and computational load while preserving the most prominent features, such as signs of vulnerabilities.

iv). Fully Connected Layer (Classification)

This layer aggregates the entire set of features extracted previously and decides on the final classification. It evaluates the probability of each class label by applying the SoftMax function. Based on the learned features, the method finally determines if the code is vulnerable or secure, which is represented by Equation (6):

$$P(y_i) = \frac{e^{z_i}}{\sum_j e^{z_j}} \quad (6)$$

In this formula, the condition software $P(y_i)$ is the probability under which the input belongs to class i, interpolated via the SoftMax function with z_i raw logit or unnormalized score class k, with the denominator containing the sum of exponentials of the logits for all possible classes. Thus, the transition from scores into a probability distribution helps the model to classify code as either vulnerable or not.

v). Loss Function (Cross-Entropy Loss)

Cross-entropy loss measures the discrepancy between true and predicted labels. It penalizes wrong predictions more than the right ones so as to improve the prediction accuracy of the model. During training, the model fits its parameters in such a way as to minimize this loss, leading to better classification and higher detection accuracy. The equation for optimizing the performance of the model using cross-entropy loss is expressed as follows in Equation (7):

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \quad (7)$$

L measures loss on the discrepancy between the observed labels y_i and the predicted probabilities $y_i$over the N samples. Logarithmically speaking, it puts an enormous penalty on the majority of wrong predictions. Such situations arise more where the model was overly confident but still wrong. This loss is hence minimized to maximize the accuracy on vulnerabilities during training.

4. Result and Discussion

This section assesses the performance of the developed deep learning model concerning software vulnerability detection and provides an overall view of its effectiveness using standard evaluation parameters. The model is tested against all Accuracy, Precision, Recall, and F1-Score-together ensuring the code segments are classified with high reliability. When preprocessing techniques were invoked along with the CNN architecture, there was a massive change in the performance of the experimental model. Such results, indeed, indicate not only the robustness of the approach per se but also its potential in real-life situations. The following subsections shall state the performance of the model and compare it with conventional methods to validate the strategies concerning overall efficiency and reliability.

4.1. Performances Metrics

Model evaluation based on established criteria such as Accuracy, Precision, Recall, and F1-Score is shown in Figure 2. The model achieves excellent Accuracy of 98.50%. Therefore, in a way, most of the inputs are rightly classified by the model. It yields a Precision of 99.10%, almost 100% in identifying code segments as being potentially vulnerable, which, in turn, would make them true positive. With the Recall being at 98.20% for catching most of the real vulnerabilities, the model receives high praise. I mean, really, F1-Score, which stands up at 98.65%, implies a pretty good trade-off especially in Favor of the precision and recall, substantiating the power and working capacity of this model to detect security weaknesses. Overall, all these results substantiate the model's readiness for the practical issue of vulnerability detection in a dependable and efficient way.

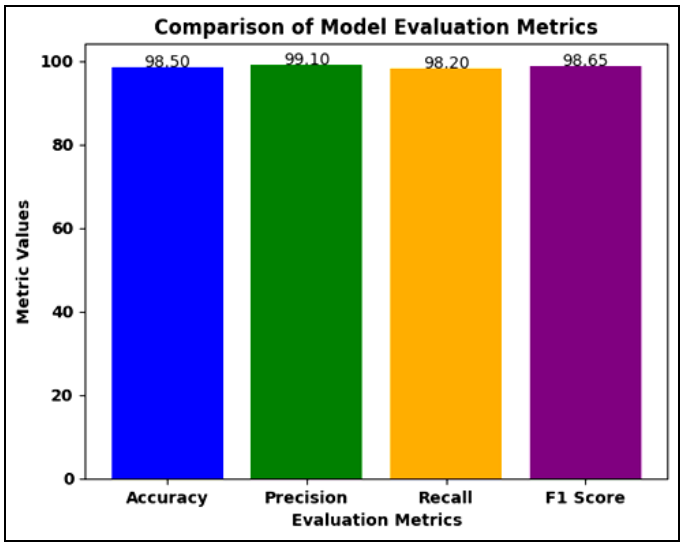

Fig 2: Comparison of Model Evaluation Metrics

5. Conclusion

The recommended approach for this research is predicated on CNN, benefiting from its process to develop a robust and scalable solution to the software vulnerability detection problem through converting the source code into structured 2D representations for deep semantic and structural feature extraction-and this eliminates the need for manual feature extraction, thus enhancing the optimization of the detection process. CNN unlike the rule-based and symbolic analysis of existing approaches can identify complex and dormant vulnerabilities at minimal human involvement. Experimental results demonstrate that the model exhibits potency, with accuracy and precision of up to 98.5% and 99.1%, respectively, in identifying vulnerabilities with minimum false positives, further attesting to the method's reliability for real-world applications and provision of an intelligent homemade automated framework to shield the software systems against dynamically changing cyber threats. Future work may be geared towards the extension of the model by complementing it with recurrent neural networks (RNNs) or transformer-based architectures to capture long-range dependencies in code. Besides, diversity of programming languages and vulnerability types can be widened in the dataset to appreciate the generalizability and robustness.

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