UNDERGRADUATE THESIS

CODEBERT WITH TRANSFER LEARNING FOR CROSS-SITE SCRIPTING VULNERABILITY DETECTION IN SOURCE CODE

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PREFACE

Praise and gratitude I offer to the Almighty God, Allah SWT, for through His grace and blessings, I have been able to complete this thesis entitled " Codebert with Transfer Learning for Cross-Site Scripting Vulnerability Detection in Source Code."

I am aware that the process of preparing this thesis involved assistance and support from various parties. Therefore, I would like to express my sincere appreciation to:

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ABSTRAK

Cross-site scripting (XSS) masih menjadi masalah kritis dalam keamanan web, karena penyerang memanfaatkan kerentanan dalam aplikasi web untuk menjalankan skrip berbahaya, yang mengakibatkan pelanggaran keamanan yang serius. Metode keamanan tradisional sering kali kurang efektif dalam mendeteksi serangan XSS yang canggih, menghasilkan tingkat deteksi palsu yang tinggi dan kerentanan yang terlewat. Untuk mengatasi kekurangan ini, tesis ini meningkatkan CodeBERT, model bahasa yang telah dilatih sebelumnya, dengan menyetel ulang menggunakan dataset khusus yang dirancang untuk meningkatkan identifikasi kerentanan XSS. Pendekatan ini bertujuan untuk secara signifikan mengurangi deteksi palsu dan memperkuat keamanan aplikasi web.

Untuk mengatasi masalah kritis ini, tesis ini mengusulkan pendekatan inovatif menggunakan CodeBERT, model bahasa yang telah dilatih sebelumnya, yang ditingkatkan dengan pembelajaran transfer. Metodologi ini melibatkan pengumpulan dan prapemrosesan dataset kode aplikasi web yang beragam, diikuti dengan penyetelan ulang lapisan atas CodeBERT untuk mengkhususkan dalam pengenalan pola XSS. Pendekatan ini memanfaatkan kemampuan pemahaman bahasa lanjutan CodeBERT untuk meningkatkan akurasi deteksi serangan XSS.

Evaluasi model CodeBERT yang telah disetel ulang menunjukkan kinerja yang luar biasa, terutama pada dataset PHP, di mana ia secara signifikan mengungguli pendekatan terkini sebelumnya. Model ini mencapai akurasi, presisi, recall, dan skor F1 yang tinggi, menunjukkan kemampuannya untuk meminimalkan negatif palsu yang mana sebuah atribut penting dalam konteks tugas-tugas yang berhubungan dengan keamanan. Kontribusi yang diharapkan dari penelitian ini adalah peningkatan substansial dalam deteksi XSS, yang berpotensi mempengaruhi strategi keamanan siber di masa depan.

Kata kunci: Kerentanan XSS, CodeBERT, Transfer learning, Keamanan aplikasi web, Keamanan siber

CODEBERT WITH TRANSFER LEARNING FOR CROSS-SITE SCRIPTING VULNERABILITY DETECTION IN SOURCE CODE

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ABSTRACT

Cross-site scripting (XSS) remains a critical issue in web security, as attackers exploit vulnerabilities in web applications to execute malicious scripts, leading to severe security breaches. Traditional security methods often fall short in detecting sophisticated XSS attacks, resulting in high rates of false detections and overlooked vulnerabilities. To address these shortcomings, this thesis enhances CodeBERT, a pre-trained language model, by fine-tuning it with a custom dataset specifically designed to improve XSS vulnerability identification. This approach aims to reduce false detections significantly and strengthen web application security.

To address this critical issue, this thesis proposes an innovative approach employing CodeBERT, a pre-trained language model, augmented with transfer learning. The methodology involves collecting and preprocessing a diverse dataset of web application code, followed by fine-tuning CodeBERT's upper layers to specialize in XSS pattern recognition. This approach capitalizes on CodeBERT's advanced language understanding capabilities to enhance the detection accuracy of XSS attacks.

The evaluation of the fine-tuned CodeBERT model demonstrates exceptional performance, particularly on PHP datasets, where it significantly outperforms previous state-of-the-art approaches. The model achieves high accuracy, precision, recall, and F1-scores, showcasing its ability to minimize false negatives which is a crucial attribute in the context of security-related tasks. The expected contribution of this research is a substantial improvement in XSS detection, potentially influencing future cybersecurity strategies.

Key words: XSS vulnerabilities, CodeBERT, Transfer learning, Web application security, Cybersecurity

CHAPTER I

INTRODUCTION

1.1 Background

Cross-site scripting (XSS) continues to pose a significant challenge in web security, with perpetrators exploiting web application vulnerabilities to execute harmful scripts, leading to severe security breaches. Despite heightened awareness since the early 2000s, the complexity and threat level of XSS attacks have escalated, serving as a conduit for more sophisticated cyber threats such as DDoS attacks and session hijackings.

The enduring presence of XSS vulnerabilities is well-documented, with 2018 reports indicating that XSS issues represent approximately 12% of all reported web application vulnerabilities, amounting to over 12,216 instances (Sarmah, et al., 2018). This is corroborated by the OWASP 2013 report, which ranks XSS within the top three web application security risks, underscoring the long-standing and severe nature of these threats [OWASP, 2013].

The impact of XSS attacks on users and organizations can be significant, leading to a range of consequences from data theft to reputational damage. For individual users, XSS attacks can result in the compromise of personal information, such as login credentials, financial data, and sensitive personal details, leading to identity theft, unauthorized transactions, and privacy violations (Hansen, 2020). The psychological impact on users, including stress and loss of trust in digital platforms, can also be substantial (Jones & Gupta, 2021).

Organizations affected by XSS attacks may face legal repercussions, including lawsuits and regulatory fines, especially if they are found to be in violation of data protection laws such as the General Data Protection Regulation (GDPR) (Williams, 2019). The loss of customer trust and loyalty can be particularly damaging, as it can lead to a decline in business and revenue (Smith & Johnson, 2020). Additionally, organizations

often incur substantial financial costs associated with breach remediation, cybersecurity enhancements, and downtime during recovery efforts (Brown & Green, 2021).

High-profile XSS incidents underscore the severity of these attacks. For example, in 2017, British Airways' website fell victim to an XSS attack that compromised the personal and financial information of approximately 380,000 customers (Martin et al., 2019). This breach not only resulted in direct financial losses but also led to a significant drop in the airline's stock price and a damaged reputation. Similarly, in 2018, an XSS vulnerability in eBay's website allowed attackers to embed malicious scripts in listings, potentially exposing millions of users to fraud (Curphey & Araujo, 2020). The incident raised concerns about the e-commerce giant's security measures and the safety of its online marketplace.

Another notable example is the 2019 XSS attack on the social media platform Twitter, where a security researcher demonstrated how a tweet containing malicious JavaScript code could execute on a user's browser, potentially leading to account compromise and data theft (Smith, 2020). These incidents highlight the urgent need for robust XSS detection and prevention mechanisms to protect against the far-reaching consequences of such attacks, emphasizing the importance of ongoing research and development in web security technologies.

Conventional methods for detecting XSS attacks have been inadequate, struggling to keep up with the evolving complexity of attack techniques. This insufficiency is highlighted by the findings of Wang, et al. (2022), who discovered that XSS attack detection models based on machine learning and deep learning are susceptible to adversarial attacks, exhibiting an escape rate of over 85%. The exposure of these vulnerabilities underscores the pressing need for advancements in detection methods. Furthermore, traditional static analysis tools like ProgPilot, Pixy, RIPS, and AppScan have shown limited effectiveness in detecting XSS vulnerabilities comprehensively, often missing vulnerabilities or generating high rates of false positives. For instance, Maurel et al. (2021) report that these tools only achieve detection rates of approximately 40-60%, with false positive rates as high as 30-50%. This empirical evidence demonstrates that deep learning models significantly outperform traditional tools, revealing the

inadequacies of conventional methods and the necessity for innovative approaches like those leveraging advanced neural network architectures.

In the quest for more effective XSS detection approaches, the potential of CodeBERT, augmented with transfer learning, has emerged as a promising solution. CodeBERT's innovative architecture, which interprets the intricacies of both programming languages and natural language, offers a significant advancement in analyzing the complex content of web application source code. The effectiveness of CodeBERT has been demonstrated in recent research by Mashhadi and Hemmati (2021), where it was employed for automated program repair of Java bugs. Their approach, fine-tuned on extensive datasets, showed CodeBERT's ability to generate developer-level fix codes with high efficiency, addressing diverse bug types without the constraints of previous tools, such as token length or vocabulary limitations. This success is evidenced by their model's accuracy rates of 72% on large duplicate datasets and 68.8% on small duplicate datasets, and 23.27% on large unique datasets and 19.65% on small unique datasets, which far exceed those achieved by a simple seq2seq baseline model. This success in automated repair tasks suggests a strong potential for applying CodeBERT to the realm of XSS vulnerability detection, where such adaptability and precision are crucially needed.

This progressive approach not only meets current security demands but also paves the way for the future of threat detection, highlighting the capabilities of advanced language models like CodeBERT in strengthening web defenses. It underscores the critical importance of continuous research and development in the fields of Natural Language Processing (NLP) and code analysis, ensuring that security measures keep pace with the sophistication of potential cyber threats.

1.2 Research Problem

The central challenge this thesis addresses is the inadequate detection of XSS vulnerabilities by traditional security methods, which often miss sophisticated XSS attacks, leading to high false detections. This research seeks to enhance CodeBERT’s performance specifically for XSS vulnerability identification by fine-tuning the model

with a custom dataset and Transfer Learning, aiming to significantly reduce false detections and strengthen web application security.

1.3 Research Scope

1. Data for this study will be sourced from publicly available web application code that primarily focuses on source code written in prevalent web programming languages such as Node.js and PHP with a focus on those susceptible to XSS attacks (Maurel et al., 2021).
2. The analysis will utilize CodeBERT combined with transfer learning, a novel approach in NLP, to interpret and analyze the source code more effectively.
3. The study aims to include a substantial dataset for robust analysis, targeting a minimum of 1,000 code instances to ensure comprehensive coverage and reliability.

1.4 Research Objective

The primary aim of this research is to develop a robust system for detecting XSS vulnerabilities in web application source code using CodeBERT with transfer learning. This approach capitalizes on CodeBERT's advanced language understanding capabilities to enhance the detection accuracy of XSS attacks. The study will prioritize the development of an efficient detection system, assessing its performance in terms of accuracy and false-positive rates. By focusing on the implementation of CodeBERT with transfer learning, this research aims to offer a practical solution to improve web application security against XSS attacks.

1.5 Research Benefits

1. Improving the security of web applications by effectively reducing the risk of XSS attacks.
2. Enhancing understanding of the applicability of NLP techniques like CodeBERT can be innovatively applied in the cybersecurity domain, particularly in identifying complex security vulnerabilities.

3. Demonstrating the effectiveness of CodeBERT in automated vulnerability detection.

CHAPTER II

LITERATURE REVIEW

The detection of XSS attacks has seen significant advancements, with researchers exploring a range of methodologies to address the increasingly complex threat landscape. This section presents an overview of key studies in the domain, emphasizing their contributions, outcomes, and relevance to the proposed research on CodeBERT with transfer learning for XSS vulnerability detection.

Wang et al. (2010) were among the first to employ structural learning in understanding XSS attacks, setting the stage for future research in the area. Their methodology involved analyzing attack vectors using structural learning techniques, offering insights into the intricacies of XSS scenarios. Their findings demonstrated the potential of structural learning in identifying and comprehending various XSS attack vectors, underscoring the necessity for sophisticated detection approaches.

Expanding on Wang et al.'s foundational work, Halfond et al. (2011) proposed a comprehensive approach to XSS detection by integrating static and dynamic analysis in penetration testing. Their approach highlighted the significance of examining source code and executing it in controlled environments, leading to improved accuracy in detecting XSS vulnerabilities. Their findings indicated enhanced detection rates compared to conventional methods, showcasing the efficacy of their comprehensive approach.

Stepien et al. (2012) illustrated the use of TTCN-3 for web penetration testing, presenting specialized methodologies for managing and automating testing processes. Their findings emphasized the advantages of automating testing processes, such as increased efficiency and improved testing accuracy, underscoring the importance of streamlining XSS detection efforts.

The trend towards autonomous solutions in XSS detection became apparent in the work of Goswami et al. (2017), who introduced an unsupervised method for detecting XSS attacks. Their approach aimed to develop systems capable of learning and adapting autonomously, reflecting a shift towards more intelligent detection mechanisms. Their

findings showed promising performance in detecting previously unknown XSS attack patterns, highlighting the potential of unsupervised learning in enhancing XSS detection capabilities.

Rathore et al. (2017) explored the use of machine learning classifiers for XSS detection within Social Networking Services (SNSs), emphasizing the ability of machine learning algorithms to recognize complex XSS patterns. Their findings demonstrated notable improvements in detection accuracy compared to traditional rule-based approaches, indicating the effectiveness of machine learning in augmenting traditional detection methods.

More recently, Confido et al. (2022) have adopted AI-driven methods in penetration testing, underlining the pivotal role of AI in adapting to evolving XSS threats. Their work signifies a shift towards more proactive and intelligent defense mechanisms, aligning with the proposed research on CodeBERT with transfer learning. Their findings showcased the effectiveness of AI-driven methods in identifying and mitigating XSS vulnerabilities, highlighting the potential of AI in enhancing web application security.

In summary, the evolution from structural learning to AI-driven approaches indicates a trend towards automated, intelligent XSS detection methods. These advancements not only address the complexity of modern web applications but also set the stage for future developments in cybersecurity. Table 2.1 provides a comparative overview of various XSS detection methods, underscoring the progression towards the advanced application of CodeBERT with transfer learning, as proposed in this research.

Table 2.1 Comparison of Previous Research

No	Researcher	Topic	Methods	Comparison with CodeBERT Method
1	Wang et al. (2010)	Structural Learning of Attack Vectors	Attack vector generation	CodeBERT applies context and semantic analysis beyond vector generation.

2	Halfond et al. (2011)	Static and Dynamic Analysis in Penetration Testing	Combination of static and dynamic analysis	CodeBERT identifies complex vulnerabilities beyond static/dynamic scope.
3	Stepien et al. (2012)	Using TTCN-3 for Web Penetration Testing	TTCN-3 for modeling web penetration testing	CodeBERT learns from real XSS data, not limited to predefined models.
4	Goswami et al. (2017)	Unsupervised Method for Detection of XSS Attack	Unsupervised learning techniques	CodeBERT utilizes labeled data for higher precision and recall.
5	Rathore et al. (2017)	Machine Learning Classifier on SNSs for XSS Attack Detection	Machine learning classifiers	CodeBERT automates feature learning, potentially increasing accuracy.
6	Confido et al. (2022)	AI in Penetration Testing	AI-driven penetration testing	CodeBERT offers a targeted approach specifically for XSS vulnerabilities.

The Table 2.1 illustrates the evolution of XSS attack detection methods, with a focus on the incremental improvements leading up to the use of CodeBERT. Each method introduced by researchers over the years has contributed to the complexity of understanding and preventing XSS vulnerabilities. CodeBERT stands out in this progression as a tool that not only learns from real XSS data but also utilizes labeled data to increase precision and recall. It offers a targeted approach by automating feature learning, which enhances accuracy and tailors the detection process to the specific challenges of XSS vulnerabilities. This comparison underscores the importance of developing more sophisticated, AI-driven methods to keep pace with the constantly evolving security landscape.

CHAPTER III

THEORITICAL BASIS

3.1 Cross-Site Scripting (XSS)

Cross-site Scripting (XSS) is a prevalent and pernicious attack at the application layer, where attackers inject malicious code into web applications to target users. These attacks exploit vulnerabilities to inject untrusted content into a trusted context, deceiving a user's web browser into executing the code as if it were a legitimate part of the application. This can result in unauthorized actions, data theft, and a breach of user privacy. XSS vulnerabilities primarily stem from inadequate validation of user input and the absence of sanitization routines within the web application, allowing for raw, unvalidated input to be reflected in output. JavaScript is commonly exploited in XSS attacks due to its widespread use on the internet, with over 93.6% of websites utilizing it (Sarmah et al., 2018).

The first and perhaps most crucial precondition is injectability. It involves the attacker's ability to use an attack vector to inject a malicious script—often JavaScript—into a vulnerable web application. Attack vectors are how attackers deliver their malicious payload, exploiting known vulnerabilities to gain unauthorized access to sensitive information or manipulate user actions. As web applications become increasingly interactive, the potential for such attack vectors grows exponentially.

For instance, to test for XSS vulnerabilities, an attacker might attempt to inject a script that triggers an alert box displaying the text "XSS" when a web page is loaded. This simple test can reveal whether the application properly sanitizes user input. Attackers can use various encoding techniques or obfuscation to bypass security filters, making the script injection less detectable. Common attack vectors include the manipulation of tags such as <img>, <script>, <title>, <iframe>, <object>, and <embed> tags, each with specific attributes or contexts that can be exploited for XSS attacks.

An example of such an attack vector might look like this within an <img> tag:

```
<img src="javascript:alert('XSS');">
```

Figure 3. 1 *Example of a Cross-Site Scripting (XSS) Attack*

In this case, the src attribute is exploited to execute JavaScript, which would not be possible if the application properly sanitized user input to prevent the execution of scripts from untrusted sources.

Injectability is not limited to crafting malicious URLs or form inputs; it can also encompass more sophisticated methods, such as embedding malicious content in user comments or forum posts (stored XSS) or manipulating the Document Object Model (DOM) directly in the client's browser (DOM-based XSS).

Understanding these preconditions and the concept of injectability is vital for developing robust defenses against XSS attacks. It underscores the importance of stringent input validation and sanitization routines within web applications to prevent attackers from introducing malicious scripts into the system. By effectively blocking the injectability stage, the subsequent stages of executability and exfiltration can also be thwarted, thereby neutralizing the threat posed by XSS attacks (Sarmah et al., 2018).

3.2 Types of XSS Attacks

3.2.1 Reflected XSS Attacks

Reflected XSS, also known as Non-persistent or Type-I XSS attack, occurs when an attacker sends a crafted request with a malicious script to a vulnerable web application, which then reflects the script back in the response. The victim's browser executes this response, perceiving it as a legitimate part of the application. The attack involves tricking the user into clicking a malicious link, which sends the script to the server. The server then reflects the script back to the user's browser. The critical failure in this type of attack

is the server's inability to properly sanitize user input, allowing the script to be integrated into the response and executed by the browser (Fogie et al., 2007).

3.2.2 Stored XSS Attacks

Stored XSS, or Persistent (Type-II) XSS attack, involves the permanent storage of a malicious script on the server, such as within databases, message forums, or comment sections. Users accessing the compromised web application trigger the inclusion of this script in the page rendered by the server to the browser. As a result, every user visiting the application potentially executes the malicious script. This form of XSS is particularly hazardous due to its ability to affect multiple users and its persistence until the script is purged from the server (Kirda et al., 2006).

3.2.3 DOM-based XSS Attacks

DOM-based, or Type-0 XSS, differs as it exploits client-side vulnerabilities, specifically within the browser's Document Object Model (DOM). In this scenario, the attacker manipulates the victim’s browser environment, causing the execution of malicious scripts. Unlike Reflected and Stored XSS, where the malicious script is delivered through the server's response, DOM-based XSS attacks involve executing the script by altering the DOM environment in the client's browser. This attack type highlights vulnerabilities in the client-side scripting interpreter rather than server-side flaws (Pellegrino et al., 2017).

3.3 Natural Language Processing (NLP)

Natural Language Processing (NLP) is a branch of artificial intelligence that focuses on the interaction between computers and human language. It encompasses the processes of reading, deciphering, understanding, and making sense of human languages in a valuable way. By leveraging algorithms and computational techniques, NLP enables computers to process and analyze large amounts of natural language data, which can range from written text to spoken word.

The core of NLP involves the application of algorithms to identify and extract natural language rules, allowing the conversion of unstructured language data into a form that computers can understand.

Natural Language Processing (NLP) encompasses several key processes essential for understanding and interpreting human language. Tokenization involves breaking down text into words, phrases, symbols, or other meaningful elements called tokens. Parsing further analyzes the grammar of sentences to elucidate the relationships between these tokens. Semantic analysis then steps in to determine the meanings of words and how sentences are composed, providing an understanding of the overall meaning. Additionally, sentiment analysis identifies the mood or subjective opinions within the text, categorizing them as positive, negative, or neutral.

The applications of NLP are diverse and far-reaching. It plays a crucial role in language translation, bridging the gap between different languages by translating text or speech from one language to another. Sentiment analysis is widely used in assessing public opinion, market research, and monitoring social media to gauge consumer sentiments. Speech recognition, another critical application of NLP, converts spoken language into text and is integral to the functioning of voice search technologies and virtual assistants. Furthermore, NLP drives the development of chatbots and virtual assistants, enabling automation in customer service and user assistance. Lastly, text analytics, powered by NLP, is pivotal in extracting insights and information from vast volumes of text data.

Natural Language Processing (NLP) has solidified its role as a critical component within the technological realm, catalyzing a paradigm shift in machine interaction with human language. This field has driven remarkable progress in diverse sectors, including customer service, healthcare, and marketing, by enabling enhanced processing and analysis of voluminous language data. The ongoing refinement and growth of NLP technologies continue to shape machine interaction and the interpretation of complex language datasets (Jurafsky et al., 2009).

3.4 Data Preprocessing

Preprocessing is a crucial stage in data analysis pipelines, involving various steps to prepare raw data for further processing and analysis. These preprocessing steps help enhance the quality, consistency, and usability of the data, ultimately improving the performance of downstream tasks such as modeling and prediction. Some common preprocessing techniques include:

1. **Data Cleaning:** Data cleaning involves identifying and correcting errors, inconsistencies, and missing values in the dataset (Witten et al., 2011). This step ensures that the data is accurate, complete, and free from noise or irrelevant information. Techniques such as outlier detection, imputation of missing values, and removal of duplicates are commonly used for data cleaning (Witten et al., 2011).
2. **Normalization and Standardization:** Normalization and standardization are techniques used to rescale the features of the dataset to a common scale (Witten et al., 2011). Normalization typically scales the feature values to a range between 0 and 1 or -1 and 1, while standardization transforms the features to have a mean of 0 and a standard deviation of 1 (Witten et al., 2011). These techniques help mitigate the effects of varying scales and distributions in the data, making it more suitable for modeling algorithms.
3. **Tokenization:** Tokenization is the process of breaking down text data into smaller units called tokens, which can be words, phrases, or characters (Jurafsky et al., 2009). This step is essential for natural language processing tasks such as sentiment analysis, text classification, and named entity recognition. Tokenization allows the text data to be represented in a structured format that can be processed and analyzed by machine learning algorithms (Jurafsky et al., 2009).
4. **Feature Engineering:** Feature engineering involves selecting, transforming, and creating new features from the raw data to improve the performance of machine learning models (Witten et al., 2011). This may include techniques such as dimensionality reduction, feature scaling, and encoding categorical variables.

Feature engineering aims to extract meaningful information from the data and represent it in a format that is conducive to modeling (Witten et al., 2011).

5. **Text Preprocessing:** For text data, additional preprocessing steps may be required, such as removing stop words, stemming or lemmatization, and handling special characters and punctuation (Jurafsky et al., 2009). Text preprocessing helps standardize the text data and reduce its complexity, making it easier to analyze and model (Jurafsky et al., 2009).

By performing preprocessing tasks such as data cleaning, normalization, tokenization, feature engineering, and text preprocessing, raw data can be transformed into a format that is suitable for analysis and modeling. Preprocessing plays a critical role in ensuring the quality, consistency, and usability of the data, ultimately contributing to the success of data-driven applications and machine learning projects.

3.5 CodeBERT

The transformative architecture of BERT, upon which CodeBERT is based, is depicted in the provided Figure 3.1. BERT's structure, known as Bidirectional Encoder Representations from Transformers, represents a significant leap in the field of NLP, primarily due to its ability to pre-train on a broad range of language data and then fine-tune for specific tasks (Devlin et al., 2019). Figure 3.1 showcases the overall architecture of BERT, which serves as the foundation for CodeBERT's advanced capabilities in processing and understanding both natural and programming languages**.**

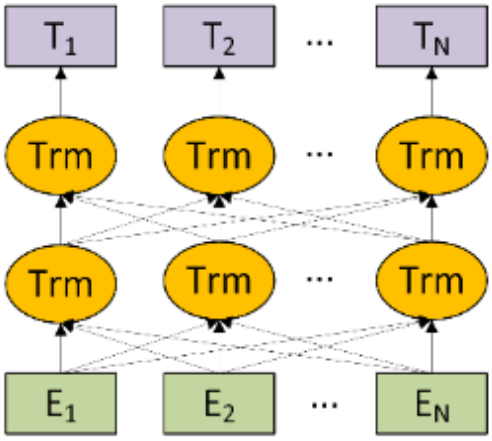

Figure 3. 2 *Overall Architecture of BERT*

(Pan et al., 2021)

At the core of CodeBERT's functionality is the tokenization process, handled by the RoBERTaTokenizer. Tokenization is the first step in transforming raw text into a format that can be processed by the model. This process involves converting the raw input text into tokens that can be embedded into numerical vectors. The RoBERTaTokenizer extends the capabilities of the original BERT tokenizer by using a byte-level Byte-Pair Encoding (BPE), which is particularly effective for handling programming languages due to its ability to manage a wider range of character combinations found in source code (Liu et al., 2019). BPE is a data compression technique that iteratively replaces the most frequent pair of bytes in a sequence with a single, unused byte. In the context of RoBERTaTokenizer, this technique is applied not just to bytes but to sequences of characters in programming languages, allowing the tokenizer to effectively handle new or uncommon tokens that are not covered by the fixed vocabulary. The process can be described by the following formula:

(3.1)

$$V_{new} = \underset{(C_o C_j) \in V}{argmax}\ Count(C_i C_j)$$

In Equation 3.1, V is the vocabulary, C_i and C_j are consecutive characters in the training data, $Count(C_i C_j)$ is the frequency of their occurrence, and V_{new} is the new token added to the vocabulary. Each iteration of this process merges the most frequent pair of characters or character sequences, thereby generating a new token. This merging continues until a specified vocabulary size is reached or no more frequent pairs can be combined. The implementation of BPE in RoBERTaTokenizer optimizes the original BPE process to better suit the needs of both natural language and source code tokenization (Sennrich et al., 2016; Liu et al., 2019).

At the bottom layer, the input embeddings E1, E2, ..., En represent the encoded version of the input tokens. These tokens could be words in a sentence or tokens in a source code snippet. Each input token is converted into a numerical vector representation, known as an embedding, which captures the semantic and syntactic information of that token. The embedding process typically involves looking up the token in a pre-trained embedding matrix, where each token is associated with a high-dimensional vector. This allows the model to represent the meaning and relationships between the input tokens. The size of the input embeddings is usually a hyperparameter, with common sizes ranging from 128 to 768 dimensions. Formally, the input token embeddings are computed as (Devlin et al., 2019) given by Equation 3.1.

(3.2)

$$E = E_{token} + E_{segment} + E_{position}$$

In Equation 3.1, E_token is the token embedding, E_segment is the segment embedding, and E_position is the position embedding. The segment embedding is used to differentiate between different segments of the input (e.g., question and answer), while

the position embedding encodes the relative or absolute position of the token within the sequence.

In the central section, there exist numerous transformer blocks (indicated as Trm), serving as the fundamental building blocks of the BERT architecture. These transformer blocks employ attention mechanisms to concurrently handle the input embeddings, allowing the model to encompass the complete context of a token within a sequence. Each transformer block consists of multiple attention heads, where each head learns to focus on different parts of the input sequence to capture contextual information. The attention mechanism allows the model to weigh the importance of different parts of the input sequence when generating the output, rather than treating the input as a fixed sequence. Formally, the attention mechanism can be expressed as (Devlin et al., 2019) given by Equation 3.2.

(3.3)

$$Attention(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_v}})V$$

In Equation 3.2, the formula involves three key matrices: queries (Q), keys (K), and values (V). The process starts with calculating the dot product of the queries and the transposed keys (QK^T), which effectively measures the degree of alignment or similarity between all pairs of queries and keys. To prevent overly large values from the dot product, which can lead to computational instability during training due to small gradients in the softmax step, the dot products are scaled down by the square root of the dimensionality of the key vectors ($\sqrt{d_k}$).

Following the scaling, a softmax function is applied to convert the scaled scores into probabilities that sum to one. These probabilities determine the weighting of the values, effectively deciding how much each value in the sequence should contribute to the output. The final step involves multiplying this softmax output by the values matrix (V), which aggregates the values based on these weights to produce the final output of the attention mechanism. This output reflects a weighted sum of the values, where the weights are

informed by how well the corresponding keys and queries matched, allowing the model to focus attentively on the most relevant parts of the input data.

The number of transformer blocks is also a hyperparameter, with the original BERT model having either 12 or 24 transformer blocks, depending on the model size.

At the top, the transformer outputs T1, T2, ..., TN serve as the contextualized representations of each token. These output vectors contain rich contextual information gathered from the entire input sequence. The bi-directional nature of BERT means that each output vector is informed by the tokens that precede and follow it in the sequence. The size of the transformer outputs is typically the same as the input embeddings, as the model learns to generate contextualized representations of the same dimensionality as the input.

CodeBERT inherits this architecture and extends it to include the understanding of programming languages. This extension allows CodeBERT not only to grasp natural language nuances but also to interpret and analyze source code effectively. The figure underscores the layered and interconnected nature of BERT's architecture, highlighting the complexity and power of transformers in processing sequential data, which is pivotal in CodeBERT's application to tasks such as software defect prediction (Pan et al., 2021).

3.5.1 CodeBERT Algorithm

Microsoft's CodeBERT represents a cutting-edge advancement in natural language processing, developed by Microsoft specifically for code-related tasks (Feng et al., 2020). The passage states that with its ability to comprehend and generate code, CodeBERT has become a cornerstone in various applications such as code summarization, translation, and generation.

To leverage the full potential of the CodeBERT model, a structured approach is essential. The algorithm presented in this context provides a step-by-step guide for the effective utilization of CodeBERT, encapsulating the fine-tuning and inference processes (Feng et al., 2020). The comprehensive pseudocode outlined in Algorithm 1 details the steps involved in data preprocessing, model initialization, training, evaluation, and

testing, offering a robust framework for harnessing the capabilities of CodeBERT in enhancing code-related applications.

ALGORITHM 1 PSEUDO-CODE FOR CODEBERT ALGORITHM

Input:

- ***Input sequence****: x = {x1, x2, ..., xn}.*
- ***Target sequence:*** *y = {y1, y2, ..., ym}.*
- ***Model parameters:*** *θ*

Output:

- *Trained CodeBERT model.*

Tokenize *the input sequence x and the target sequence y using the CodeBERT tokenizer.*
Encode *the tokenized sequences into input IDs and attention masks.*
Load *CodeBERT Model (M_type, M_path)*
For *each training epoch:*
    For *each training batch:*
        Pass *the input IDs and attention masks through the CodeBERT model to get the output logits.*
        Compute *the loss between the output logits and the target sequence.*
        Backpropagate *the loss and update the model parameters θ using an optimizer (e.g., AdamW).*
Evaluate *the trained CodeBERT model on a validation set.*
    Compute evaluation metrics such as perplexity and BLEU score.
    Save the model checkpoint with the best validation performance.
Test *the saved model checkpoint on a held-out test set.*
    Compute *test metrics and report the final performance.*
Return *the trained CodeBERT model.*
end

The presented Algorithm 1 outlines a comprehensive procedure for training and evaluating the CodeBERT model, a cutting-edge language model developed by Microsoft. The algorithm takes as input the following components:

- Input sequence (x): A sequence of tokens representing the input data.
- Target sequence (y): A sequence of tokens representing the desired output or target data.
- Model parameters (θ): The trainable parameters of the CodeBERT model.

The output of the algorithm is the trained CodeBERT model.

The key steps in the CodeBERT algorithm are:

1. **Tokenization**: The input sequence (x) and target sequence (y) are tokenized using the CodeBERT tokenizer, which converts the text into a sequence of token IDs and attention masks.
2. **Encoding**: The tokenized sequences are encoded into a format that can be processed by the CodeBERT model, such as input IDs and attention masks.
3. **Model Initialization**: The CodeBERT model is initialized with the pre-trained weights, which provide a strong foundation for the subsequent training process.
4. **Training Loop**: The model is trained for a specified number of epochs, where in each epoch, the training data is processed in batches. For each batch:
    - The input IDs and attention masks are passed through the CodeBERT model to obtain the output logits.
    - The loss between the output logits and the target sequence (y) is computed.
    - The gradients are backpropagated, and the model parameters (θ) are updated using an optimizer, such as AdamW.
5. **Evaluation**: After each training epoch, the trained CodeBERT model is evaluated on a validation set. Evaluation metrics, such as perplexity and BLEU score, are computed. The model checkpoint with the best validation performance is saved for the final testing.
6. **Testing**: The saved model checkpoint is tested on a held-out test set, and the final performance metrics are reported.
7. **Output**: The trained CodeBERT model is returned as the final output of the algorithm.

This structured approach provides a comprehensive framework for effectively leveraging the CodeBERT model for various code-related tasks and applications, such as code summarization, translation, and generation.

3.6 Transfer Learning

Transfer learning is a sophisticated technique in machine learning that capitalizes on the knowledge acquired from one problem and applies it to solve another, yet related, problem. This strategy is particularly beneficial when the target task is data-deficient, especially in terms of labeled information, which is typically costly or labor-intensive to obtain. The essence of transfer learning lies in the principle that certain learned features or knowledge are general enough to be transferred across different domains (Bengio et all., 2012).

The transfer learning process typically begins with a pre-trained model that has been developed using a large and labeled dataset within the source domain. During this pre-training phase, the model learns a wide array of features and representations that capture the intrinsic patterns and structures of the data. These learned features embody a form of general knowledge that can be applied to a target task, making them invaluable for transfer learning applications.

Figure 3.2 illustrates the typical process of network-based deep transfer learning, highlighting the stages from a pre-trained model through fine-tuning to the final application of the fine-tuned model.

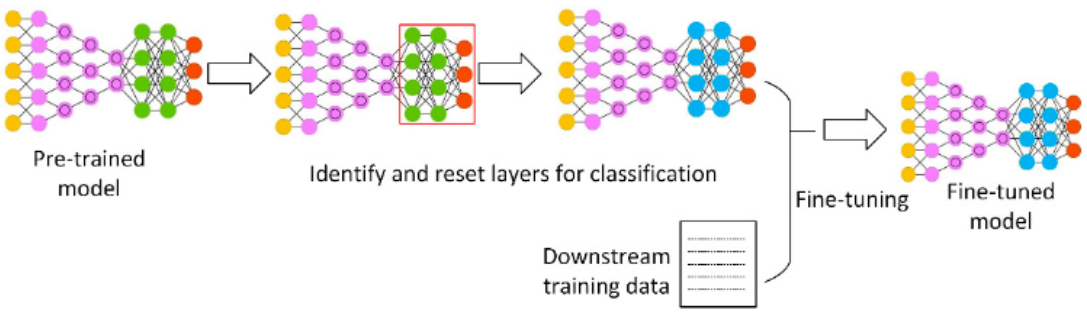

Figure 3. 3 *A typical process of network-based deep transfer learning (Pan et al., 2021)*

As illustrated in the Figure 3.2, after pre-training, the model is fine-tuned using a smaller, labeled dataset from the target domain. This fine-tuning phase involves adapting

the model's parameters to align with the specific characteristics and requirements of the target task. It often includes resetting certain layers of the network for the task-specific classification while leveraging the generalized representations from the pre-trained model. This process of fine-tuning ensures that the model retains valuable knowledge from the source domain and gains the ability to perform effectively in the target domain by learning task-specific nuances (Pan et al., 2021).

In practice, fine-tuning enhances the model's ability to discern and act upon the unique features of the target task, thereby refining its predictive accuracy within the target domain. Consequently, fine-tuned models demonstrate improved performance, showcasing their ability to recognize and respond to the specific features of new tasks.

Deep learning models that undergo transfer learning have shown remarkable success in various fields, including computer vision and natural language processing. By utilizing extensive data from pre-existing tasks, these models are equipped to tackle complex new problems, even with limited access to labeled data in the target domain. Transfer learning thus serves as a foundational approach for developing advanced models capable of learning and adapting in dynamic and data-constrained environments.

3.6.1 Transfer Learning Algorithm

Transfer learning, a pivotal technique in machine learning, leverages knowledge from a source domain to enhance performance on a related target task, particularly when labeled data in the target domain is limited. This approach is rooted in the idea that learned features or representations from one problem can be applied to another, facilitating quicker and more efficient learning. Algorithm 2 presents a pseudo-code for transfer learning, delineating the steps to fine-tune a pre-trained model on a target task using labeled data from both the source and target domains.

ALGORITHM 2 PSEUDO-CODE FOR TRANSFER LEARNING

Input:

- *Source_Data: Labeled dataset from the source domain.*
- *Target_Data: Labeled dataset from the target domain.*

- *Pre-trained_Model: Model pre-trained on the source domain.*

Fine-tuning_Params: Parameters for fine-tuning (learning rate, number of epochs, etc.).

Output:

- *Fine-tuned model for the target task.*

```
Initialize CUDA, GPU, and random seed.
Load Pre-trained_Model.
Define Freeze_Pre-trained_Layers ():
    Freeze parameters of Pre-trained_Model.
end
Define Modify_Network_Architecture ():
    Adjust the output layer to match the number of classes in the target task.
end
Define Fine-tune_Model (Pre-trained_Model, Target_Data, Fine-tuning_Params):
    Unfreeze Pre-trained_Model parameters.
    Modify_Network_Architecture ().
    Initialize Optimizer with Fine-tuning_Params.
    For each epoch in Fine-tuning_Params.epochs:
        For each batch in Target_Data:
            Forward pass batch through the model.
            Compute loss.
            Backpropagate gradients.
            Update model parameters using the optimizer.
        end
    end
end
Return Fine-tuned model.
```

The algorithm begins by initializing necessary components and loading the pre-trained model. Subsequently, it freezes the parameters of the pre-trained model to prevent them from being updated during initial training. Then, it modifies the network architecture to accommodate the characteristics of the target task. The fine-tuning phase involves unfreezing the pre-trained model, adjusting the output layer, initializing the optimizer, and iteratively updating model parameters based on the target data. Ultimately, the algorithm outputs a fine-tuned model ready for deployment in the target domain. (Pan & Yang, 2010)

3.7 Evaluation Metrics

Evaluating the performance of XSS detection models is paramount, and a suite of standard performance metrics is employed to gauge the efficacy of the proposed machine learning models accurately. Accuracy, precision, recall, and F1-score are integral to this assessment, offering a multi-dimensional view of a model's capabilities (Pan et al., 2021).

To assess the performance of the XSS detection model, the results are organized into a confusion matrix, as shown in Table 3.1

Table 3.1 Confusion Matrix

	Actual Positive	Actual Negative
Predicted Positive	True Positive (TP)	False Negative (FN)
Predicted Negative	False Positive (FP)	True Negative (TN)

The confusion matrix then leads to the calculation of:

3.7.1 Accuracy

Accuracy serves as a fundamental metric for assessing the overall effectiveness of a classification model. It is defined as the proportion of correct predictions made by the model, encompassing both true positive and true negative outcomes. The calculation of accuracy is given by Equation 3.3.

(3.3)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

In this equation:

- TP (True Positives) are instances where the model correctly predicts the positive class.

- TN (True Negatives) are instances where the model correctly predicts the negative class.
- FP (False Positives) are instances where the model incorrectly predicts the positive class.
- FN (False Negatives) are instances where the model incorrectly predicts the negative class.

Accuracy is a highly interpretable metric, offering a quick snapshot of a model's performance. A high accuracy score indicates that the model is effective in its predictions. However, this metric may not always provide a complete picture, especially in cases of imbalanced datasets. For example, in a dataset heavily skewed towards one class, a model could predict every instance as belonging to the dominant class and still achieve high accuracy, despite not genuinely capturing the underlying patterns needed for accurate classification.

Thus, while accuracy is a valuable initial indicator of model performance, it is crucial to complement it with other metrics like precision, recall, and F1-score. These additional metrics provide deeper insights into the model's performance, particularly in handling class imbalances and differentiating between classes effectively. They are vital in ensuring that the model's predictions are not only accurate but also meaningful and reliable (Tan et al., 2016).

3.7.2 Precision

Precision indicates the proportion of positive identifications that were correct, focusing on the quality of the positive predictions. The formula to calculate Precision is detailed in Equation 3.4.

(3.4)

$$Precision = \frac{TP}{TP + FP}$$

A model with high precision demonstrates a low rate of false positives, making it particularly valuable in scenarios where the consequences of falsely identifying negatives as positives are critical. For instance, in email spam detection, a high precision model would minimize important emails being misclassified as spam. In medical testing, high precision ensures that patients are not subjected to unnecessary treatments based on incorrect diagnoses.

Precision is a crucial metric when the cost of a false positive is high, but it does not consider the model's ability to identify all positive instances (i.e., it does not account for false negatives). Therefore, while a model with high precision is less likely to make a false positive error, it may still miss many actual positives. This is why precision is often used alongside recall (sensitivity) for a more comprehensive evaluation of a model's performance (Bishop, C. M., 2006).

3.7.3 Recall

Recall, also known as the true positive rate or sensitivity, is a critical metric in classification models, particularly for evaluating their capability to correctly identify positive instances. It is defined as the ratio of the number of true positives to the sum of true positives and false negatives which is illustarated in the Equation 3.5

(3.5)

$$Recall = \frac{TP}{TP + FN}$$

Recall becomes an essential metric in situations were missing out on a positive instance could have dire consequences. For example, in medical diagnosis, a high recall rate is crucial to ensure that as many patients with a disease are correctly identified as possible. In security applications, such as fraud detection, a high recall helps in identifying as many fraudulent activities as possible, even if it means facing some false positives.

While a high recall rate ensures that the model captures most of the positive cases, it does not indicate how many negative instances are incorrectly identified as positive. Therefore, recall is often used in conjunction with precision to achieve a balanced

perspective on the model's performance, as a model might achieve high recall but at the cost of a large number of false positives (Shalev-Shwartz et al., 2014).

3.7.4 F1-Score

The F1-score is a critical metric in the evaluation of classification models, especially when there is a need to balance precision and recall. It is particularly valuable when equal importance is given to both false positives and false negatives. The F1-score is the harmonic mean of precision and recall, providing a single metric that balances both aspects which what Equation 3.6 illustrates.

(3.6)

$$F1 - Score = \frac{2 * Precision * Recall}{Precision + Recall}$$

This measure is beneficial when dealing with imbalanced datasets where one class outweighs the other significantly. In such cases, the F1-score provides a more accurate reflection of the model's performance than accuracy alone, as it equally considers both the model's precision (its ability to correctly label positive instances) and its recall (its ability to detect all positive instances).

The F1-score is particularly useful in scenarios where it's crucial to maintain a balance between retrieving relevant instances (recall) and ensuring the relevance of what is retrieved (precision). For example, in information retrieval or disease screening, where both the retrieval of all relevant cases (high recall) and the accuracy of the retrieval (high precision) are equally important, the F1-score serves as a more comprehensive measure than considering precision or recall alone (Witten et al., 2011).

CHAPTER IV

RESEARCH METHODOLOGY

4.1 Research General Description

In response to the limitations of traditional XSS vulnerability detection methods, this research introduces an innovative approach employing CodeBERT, augmented with transfer learning, to refine and enhance the identification of security flaws within web application source code. Leveraging a curated dataset, the study aims to not only address the shortcomings of conventional techniques but also to advance the performance of the CodeBERT model, tailoring it specifically to the complex domain of web security. The research workflow, detailed in the subsequent figure, progresses through a series of methodical stages, from initial data collection to the comprehensive evaluation of the model's capabilities, ensuring a rigorous and replicable exploration of this cutting-edge methodology.

Figure 4.1 delineates the comprehensive workflow of the research, charting the path from initial data acquisition through to the final evaluation, encapsulating the strategic application of CodeBERT with transfer learning to address XSS vulnerability detection.

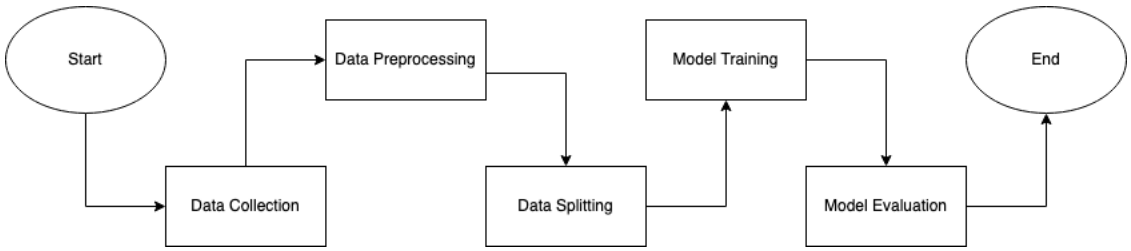

Figure 4. 1 *Research Flowchart*

4.2 Datasets

The dataset is a rich repository, openly accessible for scholarly and research purposes, containing a diverse set of Node.js and PHP code samples. These samples are carefully classified into 'safe' and 'unsafe' categories, allowing for a detailed examination of potential XSS attack vectors and the effectiveness of various defense strategies implemented within web applications.

In this research, the dataset is recreated as closely as possible to the original structure outlined by Maurel et al. (2021). The PHP and Node.js datasets are divided based on rule types, with separate databases f or mismatching instances. Furthermore, the datasets are duplicated into two variants: one with the echo_html() function applied and the other with variable names randomly renamed using the rename_randomly_variable_names() function. This approach ensures a comprehensive evaluation of the CodeBERT model's performance across different coding practices.

The PHP dataset contained a total of 23,530 samples, which were further divided into two subsets: D1-HTML and D2-echo-HTML, each containing the same number of samples as the original dataset. The Node.js dataset consisted of 24,864 samples, forming a single subset D-write-HTML. This expansive dataset not only provides a solid foundation for conducting a robust analysis of XSS vulnerabilities but also offers an average number of lines of code of 23 and 24, respectively, for the PHP databases. For the Node.js samples, only one dataset is used because the front-end code is written in the JavaScript function, as is customary in practice for Node.js code.

Below are representative examples from the dataset that illustrate the clear differentiation between secure ('safe') and vulnerable ('unsafe') coding practices in both Node.js and PHP environments, showcasing the practical applications and implications of the data provided:

```
   var http_var = require( 'http' ) ;

   var server = http_var.createServer( function ( $req , res_var ) {
       res_var.writeHead( 200, { 'Content-Type' : 'text/html' } ) ;
       res_var.write( "<!DOCTYPE html>" +
        "<html>" +
        "<title> XSS </title>" +
        "<body>"
       ) ;

       var $array = new Array() ;
       $array.push( 'safe' ) ;
       var url_var = require( 'url' );
       $array.push( url_var.parse( $req.url_var, true ).query.userData
);
       $array.push( 'safe' );
       var $tainted = $array[ 1 ] ;

                   $tainted =  parseFloat( $tainted ) ;

       res_var.write( "<div " + $tainted + "= bob />" ) ;
       res_var.write(
               "<h1>Hello World!</h1>" +
               "</div>" +
               "</body>" +
               "</html>" );
       res_var.end() ;
   } ) ;
   server.listen( 8080 ) ;
```

Figure 4. 2 *Node.js Safe Sample*

In Figure 4.2, we present a Node.js code snippet illustrating the construction of a simple HTTP server that handles requests and responds with an HTML page. This example is labeled as safe due to its handling of user input to mitigate the risk of cross-site scripting (XSS) attacks.

The server logic is encapsulated within the createServer() method of the http module, which listens on port 8080 for incoming requests. Upon receiving a request, the server prepares the response by setting the status code to 200 (OK) and the content type to 'text/html'.

The critical aspect of this snippet is the handling of user input, specifically the userData parameter extracted from the request URL. Before using this input in constructing an HTML element, the code employs parseFloat() to convert it to a floating-point number.

This conversion serves as a safety measure, ensuring that even if the input contains potentially malicious content, it will be treated as a numeric value and not executed as code.

By sanitizing and processing user input in this manner, the code effectively reduces the risk of XSS attacks. The use of parseFloat() in this context exemplifies a proactive approach to web security, emphasizing the importance of validating and sanitizing user input to prevent common security vulnerabilities.

```
   var http_var = require( 'http' ) ;

   var server = http_var.createServer( function ( $req , res_var ) {
       res_var.writeHead( 200, { 'Content-Type' : 'text/html' } ) ;
       res_var.write( "<!DOCTYPE html>" +
        "<html>" +
        "<title> XSS </title>" +
        "<body>"
       ) ;

       var $array = new Array() ;
       $array.push( 'safe' ) ;
       var url_var = require( 'url' );
       $array.push( url_var.parse( $req.url_var, true ).query.userData
);
       $array.push( 'safe' );
       var $tainted = $array[ 1 ] ;

                function addslashes ( str_var ) {
                    return ( str_var + '' ).replace( /[\\"']/g , '\\$&'
).replace( /\u0000/g , '\\0' ) ;
                }
                var $sanitized = addslashes( $tainted ) ;
                $tainted = $sanitized ;

       //flaw
       res_var.write( "<div " + $tainted + "= bob />" ) ;
       res_var.write(
                "<h1>Hello World!</h1>" +
                "</div>" +
                "</body>" +
                "</html>" );
       res_var.end() ;
   } ) ;
   server.listen( 8080 ) ;
```

Figure 4. 3 *Node.js Unsafe Sample*

In Figure 4.3, we present a Node.js code snippet that demonstrates a potential vulnerability to cross-site scripting (XSS) attacks. Unlike the safe sample, this code does not adequately sanitize user input before incorporating it into the HTML response, making it susceptible to XSS exploits.

Similar to the safe sample, the code sets up an HTTP server using the createServer() method of the http module, listening on port 8080 for incoming requests. Upon receiving a request, the server prepares the response with a status code of 200 (OK) and a content type of 'text/html'.

The critical difference lies in how user input is handled. In this case, the userData parameter extracted from the request URL is assumed to be potentially malicious and is subjected to a flawed sanitization attempt using the addslashes() function. This function is intended to escape characters that could be used in XSS attacks, such as double quotes and backslashes.

However, the addslashes() function implementation in this code is insufficient to prevent XSS attacks. It fails to escape all characters that could be used to inject malicious scripts into the HTML response. As a result, the userData parameter remains vulnerable, and when it is concatenated into an HTML element attribute (in this case), it could be exploited to execute arbitrary scripts in the context of the user's browser.

This example highlights the importance of using proper input validation and sanitization techniques to mitigate XSS vulnerabilities. Developers should employ robust sanitization libraries or functions specifically designed to handle user input securely, rather than attempting to implement their own solutions, which can lead to overlooked vulnerabilities.

```
<!DOCTYPE html>
<html>
<head>
    <title> XSS </title>
</head>
<body>
<?php
$array = array();
      $array[] = 'safe' ;
      $array[] = $_GET['userData'] ;
      $array[] = 'safe' ;
      $tainted = $array[1] ;

$tainted = (float) $tainted ;


echo "<div ". $tainted ."= bob />" ;
?>
<h1>Hello World!</h1>
</div>
</body>
</html>
```

Figure 4. 4 *PHP Safe Sample*

In Figure 4.4, we present a PHP code snippet that demonstrates a safe implementation, mitigating the risk of cross-site scripting (XSS) attacks. This code sanitizes user input before using it in the HTML response, ensuring that any potentially malicious scripts are neutralized.

The code begins with the usual HTML structure, including a doctype declaration, <html>, <head>, and <body> tags. Inside the <body> tag, PHP code is embedded within <?php ... ?> tags, allowing for server-side processing of the script.

The PHP code initializes an array $array and populates it with three elements: the string 'safe', the user input from the 'userData' parameter (accessed through $_GET['userData']), and another 'safe' string. The user input is then retrieved from the array and assigned to the variable $tainted.

Before using $tainted, the code explicitly casts it to a float using (float) to ensure that it is treated as a numerical value. This step is crucial for preventing any unintended interpretation of the input as HTML or JavaScript code.

Finally, the sanitized value of $tainted is concatenated into an HTML attribute within a element. This usage is safe because the input has been properly sanitized and validated, reducing the risk of XSS vulnerabilities.

This example demonstrates best practices for handling user input in PHP to mitigate XSS vulnerabilities. Proper input validation and sanitization are essential to ensure the security of web applications.

```
   <!DOCTYPE html>
   <html>
   <head>
   <title> XSS </title>
   <script>
   <?php
   $array = array();
         $array[] = 'safe' ;
         $array[] = $_GET['userData'] ;
         $array[] = 'safe' ;
         $tainted = $array[1] ;

   $tainted = (float) $tainted ;

       //flaw

   echo "window.setInterval('". $tainted
."');" ;
   ?>
    </script>
   </head>
   <body>
   <h1>Hello World!</h1>
   </body>
```

Figure 4. 5 *PHP Unsafe Sample*

In Figure 4.5, we present a PHP code snippet that demonstrates an unsafe implementation, potentially vulnerable to cross-site scripting (XSS) attacks. This code snippet fails to properly sanitize user input before using it in a JavaScript context, creating a security risk.

The code begins with the usual HTML structure, including a doctype declaration, <html>, <head>, and <body> tags. Inside the <head> tag, a <script> block contains PHP code embedded within <?php ... ?> tags, allowing for server-side processing of the script.

The PHP code initializes an array $array and populates it with three elements: the string 'safe', the user input from the 'userData' parameter (accessed through $_GET['userData']), and another 'safe' string. The user input is then retrieved from the array and assigned to the variable $tainted.

Before using $tainted, the code explicitly casts it to a float using (float) to ensure that it is treated as a numerical value. However, the subsequent usage of $tainted in the window.setInterval() function call is dangerous. This function allows for the execution of arbitrary JavaScript code at regular intervals, making it a potential vector for XSS attacks if not properly sanitized.

In this example, if the user input contains malicious JavaScript code, it will be executed in the context of the user's browser, leading to potential security vulnerabilities. Proper input validation and sanitization are crucial to prevent such vulnerabilities in web applications.

4.3 Setups

The equipment used in this research includes computational resources for data processing, model training, and evaluation. Specifically, a high-performance computing environment with sufficient processing power and memory is employed to handle the dataset and run the CodeBERT model. For software, the research utilizes programming languages and libraries such as Python, PyTorch, and the Transformers library by Hugging Face for implementing and fine-tuning the CodeBERT model (Feng et al., 2020).

4.4 Data Preprocessing

Data preprocessing is a crucial step in the machine learning pipeline, involving the transformation of raw data into a format suitable for model training. This stage focuses on cleaning the data and extracting relevant features for the predictive modeling of XSS vulnerabilities.

1. **Simplifying the Code:**

The first step in the data preprocessing is to simplify the code by extracting specific code blocks, such as PHP or Node.js code blocks. This helps to concentrate the analysis on the sections of the code that are more likely to contain XSS vulnerabilities, rather than considering the entire application structure.

For PHP, the "Simplifying the Code" step involves using a regular expression to extract the PHP code block from the larger codebase. The regular expression searches for the PHP code enclosed within `<?php` and `?>` tags, and the extracted code is then stripped of any leading or trailing whitespace. This effectively isolates the relevant PHP code, allowing the machine learning model to focus on the code constructs and patterns that are more likely to contain XSS vulnerabilities.

In the case of Node.js, the "Simplifying the Code" step focuses on removing any single-line and multi-line comments from the codebase. This is achieved using regular expressions to identify and remove the comments, ensuring that the dataset concentrates on the actual code constructs and patterns, rather than the noise introduced by comments, which are less relevant for the detection of XSS vulnerabilities.

By applying these targeted code extraction and simplification techniques, the "Simplifying the Code" step prepares the data in a way that aligns with the requirements of the machine learning model, allowing it to focus on the most pertinent aspects of the codebase for effective XSS vulnerability detection.

2. **Standardize Code:** The code is standardized to ensure uniformity across the dataset. This process includes converting all characters to lowercase to eliminate case sensitivity, removing comments to reduce noise, and normalizing whitespace within each line to maintain consistency in code formatting.
3. **Dataset Dividing:** The dataset is divided into different variants to evaluate the model's performance under various conditions. This involves applying transformations to create diverse datasets that can be used to assess the model's robustness and generalizability.

   For the PHP dataset, two distinct variants are created:

1. **D1-HTML**: In this variant, the original PHP code structure is maintained, without any additional transformations.
2. **D2-echo-HTML**: For this variant, the HTML content outside the PHP tags is converted into PHP echo statements. This transformation emulates a common web development practice where HTML is dynamically generated within PHP scripts.

   The NodeJS dataset is also modified to create a single variant:

1. **D2-write-HTML**: In this variant, the Node.js code is wrapped in a writeHTML() function, which simulates the dynamic generation of HTML content within the Node.js application.

   In order to produce these datasets, the following functions are employed:

   1. **rename_randomly_variable_names() function:**

      This function serves a crucial role in the data preprocessing stage. It randomly alters the variable names within the code, enabling the model to evaluate its proficiency in detecting XSS vulnerabilities based on the structural composition of the code, rather than relying on the actual variable names.

      For PHP, the function identifies the variables in the code using regular expressions and replaces them with randomly generated names, such as $adqfahwasc, $nexkdhrgnz, $xefylhplqz, and $uzbdbglhym. This ensures that the model's detection capability is rooted in recognizing patterns and structures, which is essential for identifying vulnerabilities that are agnostic to variable naming conventions.

      Similarly, for Node.js, the function follows a similar approach to rename the variables randomly. This transformation helps to diversify the dataset and assess the model's ability to detect XSS vulnerabilities based on the code's structure, rather than the specific variable names used.

   2. **echo_html() function:**

      This function is designed to convert HTML content external to PHP tags into PHP echo statements. This transformation emulates a common web

development practice where HTML is dynamically outputted by PHP scripts, integrating the HTML into the PHP execution flow.

Such a transformation is pivotal for the model to be assessed in real-world scenarios, where HTML generated by PHP could potentially include XSS vulnerabilities. By converting the HTML content into PHP echo statements, the dataset is prepared to better represent the types of code structures the model may encounter in practical applications.

These functional transformations, collectively applied to the dataset, aim to fortify the model's detection mechanisms, ensuring a rigorous evaluation of its ability to safeguard web applications against XSS attacks under various code structures and patterns.

By applying these transformations, the dataset is diversified, providing different scenarios to test the model's ability to detect XSS vulnerabilities. This diversification is crucial for assessing the model's generalizability and robustness in real-world applications.

4. **Counting the Code Length and Number of Lines:** The length of the simplified code and the number of lines is counted to provide numerical features that can be used in the model. These features help in understanding the complexity and size of the code samples, which can be indicative of their susceptibility to XSS attacks.
5. **Function Counting:** The number of functions in the code is counted as a feature, as the presence of numerous functions could indicate a higher likelihood of XSS vulnerabilities. This step involves identifying and counting function definitions in the code.
6. **HTML Entity Conversion (PHP):** This feature is determined by checking the PHP code for functions that convert characters to HTML entities, which is a common practice to mitigate XSS vulnerabilities. Utilizing regex patterns, the code is scanned for functions such as htmlspecialchars() and htmlentities(). The result is a boolean feature indicating whether HTML entity conversion is being employed as a protective measure in the code sample.

7. **Security Measures Check (Node.js):** In Node.js code, a feature assessing the implementation of security measures is extracted. This includes examining the code for input validation patterns, output encoding practices, and the use of modules designed for secure user input handling. Regex is used to identify functions such as .parse() and .validate() for input validation, .escape() and .encode() for output encoding, and modules like 'validator' or 'xss-filters'. The presence of any of these security measures contributes a boolean feature to the model, signifying whether the code adheres to security best practices to thwart XSS threats.
8. **Feature Encoding:** Categorical features, such as the 'Status' of the code being 'Safe' or 'Unsafe,' are converted to numerical values to enable their use in the machine learning model. This encoding process transforms categorical data into a format that can be easily processed by the model.
9. **Feature Standardization:** Numerical features, such as code length, number of lines, and function count, are standardized to have a mean of zero and a standard deviation of one. This standardization ensures that all features contribute equally to the model's performance and helps in improving the model's convergence.
10. **Dataset Preparation**: The dataset is meticulously structured to facilitate the training of the machine learning model. A CodeDataset class is defined to interface with the dataframe holding the code samples, which encapsulates a variety of numerical features alongside the simplified code. This class utilizes a tokenizer to process the code into a format compatible with the model, adhering to a set maximum length for consistency. Each dataset item consists of tokenized code inputs, an attention mask to inform the model of relevant tokens, numerical features such as code length, line number, function count, and HTML entity conversion status, as well as the label indicating whether the code is 'safe' or 'unsafe'. This step extracts salient features pertinent to XSS detection, such as script tags and user input handling. The importance of feature selection in improving model interpretability and accuracy is detailed by Guyon et al. (2003).

This comprehensive preparation ensures that the dataset is primed for efficient and effective model training and evaluation.

The preview of the dataframe, as exhibited in Table 4.2 and Table 4.3, offers a detailed view into the initial data processing techniques applied to JavaScript code snippets. This table methodically breaks down the programming language input into tokenized and encoded forms, while also indicating the presence of critical elements such as script tags, user input, and function invocation.

Table 4.2 PHP Datafame Preview

Rule Type	Code Length	Number of Lines	Function Count	Entity Conversio n	Status
r0125	-0.076725	0.065526	0.591573	0	0

Table 4.3 NodeJS Datafame Preview

Rule Type	Code Length	Number of Lines	Function Count	Security Measures Check	Status
r0125	-0.076725	0.065526	0.591573	0	0

The preprocessed code is now ready to be encoded for model training. It is cleaner, more focused on the elements relevant to XSS detection, and structured in a way that aligns with the requirements of the CodeBERT model for effective learning.

4.4.1 Data Splitting

After the dataset has been cleaned and preprocessed, it is divided into subsets for different phases of the model training and evaluation process. The data splitting process

is based on a set of rules derived from the OWASP recommendations for XSS sanitization in various web contexts. These rules are used to categorize the samples in the dataset as follows:

Rule 0, 1, 2, 5: HTML, Attribute, and URL Encoding These rules all share a common theme of encoding untrusted user input before inserting it into the HTML structure of the web application. The key aspect is to properly encode the input to prevent it from being interpreted as HTML markup, attributes, or URLs, which could lead to the execution of unintended code (i.e., XSS vulnerabilities).

Specifically:

- **Rule 0** states that untrusted data should never be directly inserted into high-risk contexts like <script> tags or certain HTML attributes.
- **Rule 1** requires HTML encoding of untrusted input before inserting it into the main content of HTML elements.
- **Rule 2** mandates attribute encoding of untrusted input before placing it within HTML element attributes.
- **Rule 5** necessitates URL encoding of untrusted input before using it in the parameters of HTML links.

The common objective of these rules is to ensure that the untrusted user input is properly transformed into harmless character sequences that will be displayed as plain text, rather than being interpreted as executable code or markup.

Rule 3, 4: JavaScript and CSS Encoding These rules focus on the secure handling of untrusted user input when it needs to be incorporated into JavaScript or CSS contexts within the web application.

- **Rule 3** specifies that untrusted input must be JavaScript encoded before inserting it into JavaScript data values, such as event handlers or within <script> tags. This prevents the input from being treated as executable code.

- **Rule 4** requires that untrusted input be CSS encoded and strictly validated before placing it into HTML style attribute values or <style> tags. This ensures that the input is interpreted as CSS data and not as code that could potentially break out of the CSS context.

The key difference between these rules and the previous group is the focus on the specific scripting and styling languages (JavaScript and CSS) that are commonly used alongside HTML in web applications. Proper encoding is essential to maintain the separation between data and code in these contexts.

Based on these rules, the dataset is split into training, validation, and testing sets as follows:

1. **Training Set:** The training set is derived from samples categorized under Rules 3 and 4. These samples are used to train the model to recognize patterns and make predictions. Approximately 70% of the data from these rules is designated for training purposes.
2. **Validation Set:** The validation set is derived from samples categorized under Rules 0, 1, 2, and 5. This set, typically around 15% of the data, is crucial for tuning model parameters and selecting the best-performing model during the training phase. The validation set acts as a proxy for the test set but is used iteratively during model development.
3. **Testing Set:** The remaining 15% of the dataset, also derived from samples categorized under Rules 0, 1, 2, and 5, is reserved for the final evaluation. The test set provides an unbiased assessment of the model's performance and its ability to generalize to new, unseen data.

This approach to splitting the dataset ensures that the model is trained and evaluated on a diverse set of samples, reflecting various levels of adherence to OWASP recommendations. It simulates a real-world scenario where the model is trained on known data (with stricter sanitization practices) and then tested on unknown data (with a mix of strict and less strict sanitization practices) (Maurel et al., 2021).

4.5 Model Training

The model training phase of this research is centered on fine-tuning the CodeBERT model to enhance its capability for detecting XSS vulnerabilities. The fine-tuning process strategically modifies CodeBERT's upper layers, which are crucial for tailoring the pre-trained model to the specifics of the XSS detection task.

1. Model Architecture

At its core lies a meticulous design comprising pre-trained layers deeply rooted in the Microsoft CodeBERT model, as detailed by Feng et al. (2020), fortified with transformer layers and a classification head. This sturdy foundation not only ensures robustness but also sets the stage for further adaptations essential for effective vulnerability detection. Furthermore, acknowledging the nuanced demands of XSS vulnerability detection, selective fine-tuning is applied, with a focus on the upper layers of the pre-trained model. For a visual depiction of this intricate architecture, Figure 4.2 presents a comprehensive illustration of the arrangement and flow of its components, elucidating the model's design and functionality.

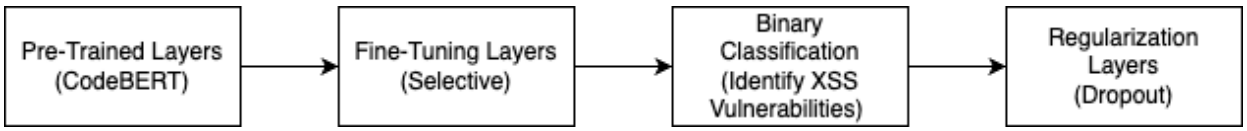

Figure 4. 6 *Model Architecture*

The architecture of the fine-tuned model for detecting XSS vulnerabilities is rooted in the pre-trained Microsoft CodeBERT model. This model, as detailed by Feng et al. (2020), is equipped with transformer layers and a classification head, providing a robust foundation for further adaptations.

In response to the challenges of XSS vulnerability detection, the model undergoes targeted fine-tuning, particularly within its upper layers. For the 12-layer CodeBERT

model used, this fine-tuning process concentrates on layers 8 to 12. Devlin et al. (2019) underline the efficacy of this method, as these layers generally capture more task-specific features, making them more adaptable to the nuances of XSS vulnerabilities. A binary classification head is subsequently incorporated to distinguish between safe and unsafe code. To maintain robustness and mitigate overfitting, the model incorporates regularization strategies, including dropout layers, following the guidelines by Srivastava et al. (2014).

2. Fine-tuning Process

- **Strategic Layer Identification**: The fine-tuning process commences with the careful identification and selection of the upper layers of the CodeBERT model. This decision is guided by established practices in transfer learning (Howard & Ruder, 2018), ensuring that the most impactful layers are optimized.
- **Calibrated Parameter Adjustment**: Once the layers are selected, a crucial step is the adjustment of learning rates. This step involves setting a reduced learning rate compared to the pre-training phase, allowing for more controlled and precise tuning of the model.
- **Balanced Training Approach**: The model is then trained over a predetermined number of epochs. This phase is delicately balanced to avoid overfitting while ensuring that the model is sufficiently trained to generalize effectively across different scenarios.
- **Robustness Through Regularization**: During this phase, dropout regularization techniques are implemented. These techniques are vital in curbing the tendency of the model to overfit and in enhancing its overall resilience.
- **Continuous Performance Evaluation**: Throughout the training process, performance metrics such as accuracy, precision, recall, and F1-score are meticulously monitored. This ongoing scrutiny is not just a measure of the model's progress, but it also provides essential insights for necessary adjustments and refinements.

By the end of the training process, the fine-tuned CodeBERT model is expected to accurately identify XSS vulnerabilities, distinguishing between safe and vulnerable code with high precision and recall. The adjustments made during the fine-tuning phase ensure that the model leverages its in-depth understanding of programming language semantics, which is critical for the nuanced task of XSS vulnerability detection.

4.6 Analysis of Results

After training the CodeBERT model, evaluating its performance is vital to ensure that it accurately detects XSS vulnerabilities. The evaluation will be based on several metrics that collectively offer a comprehensive view of the model's effectiveness.

1. **Accuracy**: The model's accuracy will be measured to determine the overall proportion of both true positives and true negatives among all the predictions made. While accuracy is a useful indicator of performance, it is not always reliable, especially in imbalanced datasets where the prevalence of one class could skew the results (Kohavi and Provost, 1998).
2. **Precision**: Precision will be assessed to evaluate the correctness of the positive predictions made by the model. A high precision indicates that the model has a low rate of false positives, which is crucial in the context of XSS detection, where false alarms can be costly (Davis and Goadrich, 2006).
3. **Recall**: Recall, or the true positive rate, will measure the model's ability to correctly identify all actual positives. This metric is essential in scenarios where it fails to detect an XSS vulnerability could have severe implications (Powers, 2011).
4. **F1-Score**: The F1-score will be calculated to balance the precision and recall of the model. It is a harmonic mean of the two metrics, providing a single score that encapsulates the model's performance in terms of both false positives and false negatives. This metric is particularly useful in situations where an equal importance is given to precision and recall, as it offers a more comprehensive measure of the model’s accuracy than evaluating precision or recall alone (Sasaki, 2007).

Each metric offers different insights into the model's performance, and when considered together, they provide a robust evaluation framework. The model will be evaluated on a separate testing set that was not seen during the training phase to ensure an unbiased assessment of its generalizability and predictive power.

4.6.1 Hyperparameter Tuning

Hyperparameter tuning plays a pivotal role in optimizing the performance of the CodeBERT model for XSS vulnerability detection. Hyperparameter tuning refers to the process of systematically searching for the ideal parameters that govern the training process of a machine learning model. These parameters, which are not learned from the data but set prior to training, significantly influence the model's learning and predictive accuracy. Proper hyperparameter tuning is expected to enhance the CodeBERT model's ability to discern intricate patterns in code, distinguishing between safe and vulnerable instances with higher accuracy. As highlighted by Probst et al. (2019), effectively tuned hyperparameters can lead to substantial improvements in a model's predictive performance, which is particularly crucial in the high-stakes domain of web security.

1. Hyperparameter Tuning Techniques

In this research, random search served as the cornerstone for hyperparameter tuning, a method acclaimed for its stochastic yet efficient exploration of vast hyperparameter spaces (Bergstra & Bengio, 2012). The efficacy of random search lies in its non-deterministic sampling, which allows for a broader and more diverse evaluation of the hyperparameter configurations, thereby increasing the probability of identifying superior solutions in a fraction of the time required for exhaustive searches.

For the PHP dataset, hyperparameters were chosen with careful consideration of their impact on transfer learning and the pre-trained CodeBERT model:

- **Batch Size**: [16, 32]. The determination of batch size was influenced by research suggesting that smaller batches provide more frequent updates and can lead to a

finer convergence by following more noisy gradients, while larger batch sizes capitalize on computational efficiency (Smith, 2017).

- **Learning Rate**: [1e-4, 5e-5, 1e-5]. The learning rate was selected to fine-tune the pre-trained neural network delicately. A small learning rate is imperative in this context to avoid disruptive updates that could nullify the transfer of learned features (Zhang et al., 2019).
- **Number of Layers to Fine-tune**: [2, 4, 6]. The decision on the number of layers to fine-tune is grounded in the depth of the task specificity. The upper layers of neural networks are often tuned as they capture more abstract representations, which are more likely to be task dependent (Yosinski et al., 2014).
- **Epochs**: [3, 4]. The number of epochs reflects a balance between underfitting and overfitting, a principle supported by the work of Prechelt (1998), who emphasized the importance of early stopping as an effective regularization strategy.

For the Node.js dataset, hyperparameters were selected with an appreciation of the unique aspects of the code structure and the nuanced differences in the optimization landscape:

- **Batch Size**: [16, 64]. A wider batch size range was chosen, informed by literature indicating that different code structures may benefit from varied gradient estimation strategies (Bottou et al., 2016).
- **Learning Rate**: [1e-3, 1e-4, 5e-4]. An elevated range of learning rates acknowledges the variability in the behavior of different programming languages during the fine-tuning process (Ruder, 2016).
- **Number of Layers to Fine-tune**: [2, 4]. The layer selection was motivated by the intent to harness the generality of the pre-trained model while aligning it closely with the intricacies of XSS detection within Node.js environments (Howard & Ruder, 2018).

- **Epochs**: [5]. An incremental number of epochs was designated based on the understanding that the Node.js code may necessitate a more profound adaptation period for the pre-trained model (Goodfellow et al., 2016).

The orchestration of these hyperparameters was guided by the dual objectives of harnessing the CodeBERT model's pre-trained capabilities and optimizing its performance for XSS vulnerability detection across PHP and Node.js codebases. The approach adopted aligns with the research emphasizing the strategic importance of hyperparameter tuning in machine learning and particularly in transfer learning scenarios (Probst et al., 2019).

2. Hyperparameter Tuning Implementation

The implementation of hyperparameter tuning in this study was methodically approached through a custom-developed function, random_hyperparameter_tuning. This function was instrumental in navigating the hyperparameter space by randomly sampling parameter combinations from a pre-specified distribution. The sampled parameters encompassed the learning rate, batch size, number of epochs, and the number of layers to fine-tune, each a critical determinant in the model's training trajectory.

With each iteration, the function initiated a new instantiation of the CodeBERT model. Fine-tuning was directed at the model’s upper layers, the sections of the neural network most responsive to task-specific nuances, aligning with insights from transfer learning research (Howard & Ruder, 2018). By selectively fine-tuning these layers, the model could adapt its pre-trained general knowledge to the specialized context of XSS vulnerability detection without losing its foundational language understanding.

The training regimen employed the AdamW optimizer, recognized for its effectiveness in handling sparse gradients and adaptive learning rates (Loshchilov & Hutter, 2017). This was coupled with the CrossEntropyLoss function, an apt choice for binary classification tasks common in security applications (Goodfellow et al., 2016). To safeguard against the overfitting phenomenon, an early stopping mechanism was

integrated, serving as a form of regularization to curtail the training when the validation loss ceased to decrease, thereby enhancing model generalizability.

A pivotal aspect of the tuning process was the validation phase, wherein each model's performance was rigorously assessed. The criterion for excellence was validation accuracy, a metric reflecting the model's precision in identifying XSS vulnerabilities. The finest model, determined by the peak validation accuracy, was preserved for posterity, along with its corresponding hyperparameters.

Post-tuning, the optimal model, endowed with the best hyperparameters, underwent a final round of evaluation on a separate test set. This phase was critical to verify the model's adeptness at generalizing to novel data, a quality indispensable for practical deployment scenarios. The hyperparameter tuning and subsequent evaluation substantiated the model's capability to be both accurate and robust, thus confirming its readiness for application in detecting XSS vulnerabilities.

CHAPTER V

IMPLEMENTATION

5.1 Data Preprocessing and Dataset Building for PHP Datasets

The data preprocessing and dataset building process for the PHP datasets is a crucial step in preparing the data for effective machine learning model training and evaluation. This phase involves several key steps, each designed to transform the raw code samples into a format that is optimized for the task of XSS vulnerability detection.

5.1.1 Extracting PHP Code Blocks

The first step in the data preprocessing is to extract the PHP code blocks from the larger codebase. This is a crucial step as it allows the model to focus on the relevant code sections that are more likely to contain XSS vulnerabilities, rather than analyzing the entire application structure.

The extract_php_code() function is used to perform this extraction task:

```
import re
def extract_php_code(code):
    match = re.search(r'\<\?php(.*?)\?\>', code, re.DOTALL)
    if match:
        return match.group(1).strip()
    else:
        return ''
df_PHP['Simplified_Code'] = df_PHP['Code'].apply(extract_php_code)
```

Figure 5. 1 *Python Function to Extract PHP Code from a String*

In Figure 5.1, the function leverages a regular expression pattern \<\?php(.*?)\?\> to search for the code enclosed within <?php and ?> tags. The re.DOTALL flag ensures that

the pattern matches across multiple lines, allowing the function to capture the entire PHP code block.

If a match is found, the function returns the extracted PHP code with any leading or trailing whitespace removed using the strip() method. If no match is found, an empty string is returned. The extracted PHP code blocks are then stored in the 'Simplified_Code' column of the df_PHP DataFrame. This step ensures that the dataset is focused on the relevant parts of the codebase, which is essential for the machine learning model to effectively learn and identify XSS vulnerabilities.

5.1.2 Dataset Diversification

To evaluate the model's performance under various conditions, the dataset is divided into different variants. This is achieved by applying two key transformations to the PHP code samples: randomly renaming variable names and converting HTML content outside PHP tags into PHP echo statements.

The rename_randomly_variable_names() function is used to randomly alter the variable names within the PHP code. This function identifies all the variables in the code using the regular expression \$\w+ and replaces them with randomly generated 5-character names. This transformation ensures that the model's detection capability is rooted in recognizing patterns and structures, rather than relying on specific variable naming conventions.

```
import pandas as pd
import random
import re
def rename_randomly_variable_names(code):
    variables = set(re.findall(r'\$\w+', code))
    for var in variables:
            new_name = '$' +
            ''.join(random.choices('abcdefghijklmnopqrstuvwxyz', k=5))
          code = code.replace(var, new_name)
    return code

def echo_html(code):
    return f'echo "{code}";'

df_PHP_D1 = df_PHP.copy()
df_PHP_D1['Simplified_Code'] =
df_PHP_D1['Simplified_Code'].apply(rename_randomly_variable_names)

df_PHP_D2 = df_PHP.copy()
df_PHP_D2['Simplified_Code'] =
df_PHP_D2['Simplified_Code'].apply(rename_randomly_variable_names).app
ly(echo_html)
```

Figure 5. 2 *Python Functions for Renaming PHP Variable Names and Generating HTML Echo Statements*

In Figure 5.2, the echo_html() function is designed to convert HTML content external to PHP tags into PHP echo statements. This transformation emulates a common web development practice where HTML is dynamically outputted by PHP scripts, integrating the HTML into the PHP execution flow. Such a transformation is pivotal for the model to be assessed in real-world scenarios, where HTML generated by PHP could potentially include XSS vulnerabilities. By converting the HTML content into PHP echo statements, the dataset is prepared to better represent the types of code structures the model may encounter in practical applications.

These functional transformations, collectively applied to the dataset, aim to fortify the model's detection mechanisms, ensuring a rigorous evaluation of its ability to safeguard web applications against XSS attacks under various code structures and patterns.

By applying these transformations, the dataset is diversified, providing different scenarios to test the model's ability to detect XSS vulnerabilities. This diversification is crucial for assessing the model's generalizability and robustness in real-world applications.

5.1.3 Code Standardization

After extracting the PHP code blocks, the next step is to standardize the code formatting across the dataset. This includes converting all characters to lowercase, removing comments, and normalizing the whitespace within each line. These standardization measures ensure that the dataset is uniform, and the model can focus on the relevant code patterns and structures, rather than being influenced by superficial differences in formatting which demonstrated in the Figure 5.3.

```
# Create the 'Code Length' column
df_PHP_D1['Code_Length'] = df_PHP_D1['Standardized_Code'].apply(len)
df_PHP_D2['Code_Length'] = df_PHP_D2['Standardized_Code'].apply(len)

# Count the number of lines in each code snippet
df_PHP_D1['Lines_Number'] =
df_PHP_D1['Standardized_Code'].apply(lambda x: len(x.split('\n')))
df_PHP_D2['Lines_Number'] =
df_PHP_D2['Standardized_Code'].apply(lambda x: len(x.split('\n')))
```

Figure 5. 3 *Calculating Code Length and Number of Lines in PHP Code*

5.1.4 Feature Engineering

The next step in the data preprocessing is to engineer relevant features from the code snippets. These features are designed to capture important characteristics of the code that may be indicative of XSS vulnerabilities.

1. Code Length and Number of Lines

The first set of features created are the code length and the number of lines in each code sample as demonstated in Figure 5.4.

```
# Create the 'Code Length' column
df_PHP_D1['Code_Length'] = df_PHP_D1['Standardized_Code'].apply(len)
df_PHP_D2['Code_Length'] = df_PHP_D2['Standardized_Code'].apply(len)

# Count the number of lines in each code snippet
df_PHP_D1['Lines_Number'] = df_PHP_D1['Standardized_Code'].apply(lambda
x: len(x.split('\n')))
df_PHP_D2['Lines_Number'] = df_PHP_D2['Standardized_Code'].apply(lambda
x: len(x.split('\n')))
```

Figure 5. 4 *Adding Code Length and Number of Lines Columns to PHP DataFrames*

Figure 5.4 illustrates the Python code used to add these metrics to the PHP DataFrames, offering a clearer view of the code's complexity and size, factors that are indicative of susceptibility to XSS attacks. These features help in assessing the potential security risks associated with the code segments.

2. Function Count

A further aspect analyzed within PHP code samples is the Function Count, which quantifies the number of functions present in each code snippet. This metric, showcased in Figure 5.5, is critical for understanding how the density of functions within the code might influence its vulnerability to XSS attacks.

```
def count_functions(code):
    function_pattern = r'\bfunction\b|\b=>\b'
    return len(re.findall(function_pattern, code))

df_PHP_D1['Function_Count'] =
df_PHP_D1['Standardized_Code'].apply(count_functions)

df_PHP_D2['Function_Count'] =
df_PHP_D2['Standardized_Code'].apply(count_functions)
```

Figure 5. 5 *Counting Functions in PHP Code*

Function Count is derived by identifying all function declarations using a predefined regex pattern in the code. This feature is calculated using the count_functions() function, which searches for matches to the pattern and returns their count. This count provides an indication of the code's complexity. Higher function counts may correlate with a greater complexity and potential for security vulnerabilities due to the increased interaction between multiple functions.

Incorporating the Function Count into the dataset enriches the analysis by allowing for an assessment of how the sheer volume of functions impacts the security risk of the code segments. This feature is particularly valuable for identifying code samples that might require more rigorous scrutiny for vulnerabilities due to their complex functional structure.

3. HTML Entity Conversion

The final feature explored in the analysis of PHP code samples is the HTML Entity Conversion. This feature, detailed in Figure 5.6, indicates whether the code utilizes HTML entity conversion, a common technique to mitigate XSS vulnerabilities.

```
def check_html_entity_conversion(code):
      pattern =
      r'htmlspecialchars\(|htmlentities\(|some_other_function\('
          return bool(re.search(pattern, code))

df_PHP_D2['HTML_Entity_Conversion'] =
df_PHP_D2['Standardized_Code'].apply(check_html_entity_conversion)
```

Figure 5. 6 *Checking for HTML Entity Conversion Functions in PHP Code*

The Python code snippet shown in Figure 5.6 adds a column to the DataFrame that records whether each code sample implements HTML entity conversion. By incorporating this feature into the dataset, the analysis benefits from deeper insights into the security practices adopted in the code, enabling a more nuanced assessment of its vulnerability to XSS attacks. This feature helps to differentiate code that is potentially safer from those that might be more susceptible to such vulnerabilities due to the absence of such protective measures.

5.1.5 Data Encoding

The initial step in the data normalization process for the PHP datasets involves converting categorical features into numerical values. This conversion is crucial for preparing the data for machine learning algorithms, which typically require numerical input to perform classifications effectively.

```
# Convert 'Status' to numerical values: Unsafe -> 0, Safe -> 1
df_PHP_D1['Status'] = df_PHP_D1['Status'].map({'Unsafe': 0, 'Safe': 1})
df_PHP_D2['Status'] = df_PHP_D2['Status'].map({'Unsafe': 0, 'Safe': 1})
# Convert 'HTML_Entity_Conversion' to numerical values: False -> 0,
True -> 1
df_PHP_D1['HTML_Entity_Conversion'] =
df_PHP_D1['HTML_Entity_Conversion'].astype(int)
df_PHP_D2['HTML_Entity_Conversion'] =
df_PHP_D2['HTML_Entity_Conversion'].astype(int)
```

Figure 5. 7 *Converting Categorical Variables to Numerical Values in PHP DataFrames*

The Python code provided in Figure 5.7 illustrates the method used for these conversions. By applying the **.**map() function to the 'Status' column and the **.astype(int)** function to the 'HTML_Entity_Conversion' column, the dataset is effectively transformed into a format that can be processed by machine learning models. This encoding ensures that all features in the dataset are represented in numerical terms, which is essential for the subsequent modeling phase.

5.1.6 Feature Normalization

The next crucial step in the data preparation process for the PHP datasets involves standardizing the numerical features, such as code length, line count, and function count. This standardization is conducted using the StandardScaler from scikit-learn, a process depicted in Figure 5.8.

```
from sklearn.preprocessing import StandardScaler

features = ['Code_Length', 'Lines_Number', 'Function_Count']
scaler = StandardScaler()
df_PHP_D1[features] = scaler.fit_transform(df_PHP_D1[features])
df_PHP_D2[features] = scaler.fit_transform(df_PHP_D2[features])
```

Figure 5. 8 *Standardizing Features in PHP DataFrames using StandardScaler*

The Python code snippet shown in Figure 5.8 outlines how the StandardScaler is applied to the selected features of the PHP datasets. The .fit_transform() method is used, which fits the scaler to the data and then transforms it. This method ensures that the scaling parameters (mean and standard deviation) are derived from the data before it is transformed according to these parameters.

This normalization step not only facilitates a more balanced and effective learning process but also enhances the reproducibility of the model by ensuring that the scale of the data does not influence its predictions. The clear presentation of the scaling steps in the figure provides a robust framework for understanding and implementing feature standardization in preparation for subsequent model training phases.

5.2 Data Preprocessing and Dataset Building for NodeJS Datasets

The data preprocessing and dataset building process for the NodeJS datasets is designed to address the specific challenges and characteristics of Node.js code, while following a similar overall approach to the one used for the PHP datasets. This phase involves several key steps tailored to prepare the Node.js code samples for effective machine learning model training and evaluation.

5.2.1 Simplifying NodeJS Code

The initial stage in processing NodeJS datasets for vulnerability detection involves simplifying the code by removing comments, both single-line and multi-line. This preprocessing step, depicted in Figure 5.9, is crucial for cleaning the data and focusing the analysis on the executable parts of the code, which are more relevant for identifying security vulnerabilities.

```
import re
def simplify_nodejs_code(code):
    # Remove single-line comments
    code = re.sub(r'//.*', '', code)

    # Remove multi-line comments
    code = re.sub(r'/\*[\s\S]*?\*/', '', code)

    return code.strip()

df_NodeJS['Simplified_Code'] =
df_NodeJS['Code'].apply(simplify_nodejs_code)
```

Figure 5. 9 *Simplifying Node.js Code*

This function in Figure 5.9 uses regular expressions to identify and remove the different types of comments commonly found in Node.js code:

1. **Single-line Comments**: The regular expression r'//.*' matches and removes any text starting with // and continuing to the end of the line.
2. **Multi-line Comments**: The regular expression r'/*[\s\S]*?*/' matches and removes any text enclosed within /* and */, allowing for the comments to span multiple lines.

After the comments have been removed, the strip() method is used to trim any leading or trailing whitespace from the simplified code.

The simplified code is then stored in the 'Simplified_Code' column of the df_NodeJS DataFrame. This step ensures that the dataset is focused on the relevant code constructs and patterns, which is essential for the machine learning model to effectively learn and identify potential XSS vulnerabilities in the NodeJS code.

5.2.2 Dataset Diversification

To robustly evaluate the model's performance across various scenarios, the NodeJS dataset undergoes a diversification process as illustrated in Figure 5.10. This involves applying key transformations to the code samples, primarily focusing on randomly renaming variables and wrapping the code in an artificial HTML/JS function.

```
import pandas as pd
import random
import re

def rename_randomly_variable_names_nodejs(code):
    variables = set(re.findall(r'\$\w+', code))
    for var in variables:
        new_name = '$' +
''.join(random.choices('abcdefghijklmnopqrstuvwxyz', k=5))
        code = code.replace(var, new_name)
    return code

def write_html_nodejs(code):
    return f'writeHTML(`{code}`);'

df_NodeJS_D2 = df_NodeJS.copy()
df_NodeJS_D2['Simplified_Code']                                          =
df_NodeJS_D2['Simplified_Code'].apply(rename_randomly_variable_names_no
dejs).apply(write_html_nodejs)
```

Figure 5. 10 *Renaming Node.js Variable Names and Generating HTML in Node.js Code*

This function in Figure 5.10 first identifies all the variables in the code using the regular expression \$\w+, which matches dollar-prefixed variable names. It then iterates through each variable and replaces it with a randomly generated 5-character variable name. This transformation ensures that the model's detection capability is rooted in recognizing patterns and structures, rather than relying on specific variable naming conventions.

The write_html_nodejs() function is responsible for wrapping the Node.js code in a writeHTML() function. This transformation emulates the dynamic generation of HTML content within the Node.js application, which is crucial for evaluating the model's

performance in real-world scenarios where XSS vulnerabilities may arise from such code structures.

The transformations are then applied to create the distinct D2WriteHTML dataset. By applying these transformations, the NodeJS dataset is diversified, providing different scenarios to test the model's ability to detect XSS vulnerabilities under various code structures and patterns. This diversification is crucial for assessing the model's generalizability and robustness in real-world Node.js applications.

5.2.3 Code Standardization

To ensure the NodeJS code samples within the dataset exhibit uniform formatting, a crucial step involves code standardization, as detailed in Figure 5.11. This standardization is achieved using a systematic approach encapsulated by the standardize_code(code) function.

```
def standardize_code(code):
    # Convert to lowercase
    code = code.lower()

    # Remove comments (simple version, may need adjustment for specific
languages)
    code = re.sub(r'//.*|/\*.*?\*/', '', code)

    # Normalize whitespace within each line
    code = '\n'.join([re.sub(r'\s+', ' ', line.strip()) for line in
code.split('\n')])

    return code

df_NodeJS_D2['Standardized_Code'] =
df_NodeJS_D2['Simplified_Code'].apply(standardize_code)
```

Figure 5. 11 *Standardizing Node.js Code*

The standardize_code() function in Figure 5.11 plays a crucial role in ensuring the uniformity of the Node.js code samples within the dataset. This function performs a series of transformations to achieve this standardization. First, it converts all characters in the code to lowercase using the code.lower() method, eliminating any case sensitivity that may exist in the original code. This step helps the model focus on the actual code constructs, rather than being influenced by differences in capitalization.

Next, the function employs regular expressions to identify and remove both single-line and multi-line comments from the code. The regular expression r'//.*' is used to locate and remove any text starting with // and continuing to the end of the line, effectively removing single-line comments. Similarly, the regular expression r'/*.*?*/' is used to identify and remove any text enclosed within /* and */, allowing for the removal of multi-line comments. By stripping away these comment sections, the function ensures that the analysis concentrates solely on the relevant code constructs, rather than being distracted by accompanying commentary.

Finally, the standardize_code() function normalizes the whitespace within each line of the code. This is achieved by replacing all consecutive whitespace characters with a single space using the regular expression r'\s+'. The line.strip() method is then applied to remove any leading or trailing whitespace from the individual lines. Once the whitespace has been normalized, the lines are rejoined using the '\n'.join() function, resulting in a standardized code snippet that is uniform in its formatting.

The standardized code is then stored in the 'Standardized_Code' column of the df_NodeJS_D2 DataFrame. This code standardization step ensures that the dataset is uniform, and the model can focus on the relevant patterns and structures in the Node.js code, rather than being influenced by superficial differences in formatting.

5.2.4 Feature Engineering

The feature engineering for the NodeJS dataset follows a similar approach to the PHP dataset, with the addition of a feature to check for the presence of security

measures in the code. These features are designed to capture important characteristics of the Node.js code that may be indicative of XSS vulnerabilities.

1. Code Length and Number of Lines

In the initial step of feature creation for analyzing NodeJS code, the focus is on determining the code length and the number of lines in each code sample, as illustrated in Figure 5.12. These metrics are vital for assessing the complexity and size of the code, which are indicative of potential security vulnerabilities.

```
# Create the 'Code Length' column
df_NodeJS_D2['Code_Length'] =
df_NodeJS_D2['Standardized_Code'].apply(len)

# Count the number of lines in each code snippet
df_NodeJS_D2['Lines_Number'] =
df_NodeJS_D2['Standardized_Code'].apply(lambda x:
len(x.split('\n')))
```

Figure 5. 12 *Calculating Code Length and Number of Lines in Standardized Node.js Code*

These features provide quantitative insights into the structural attributes of the NodeJS code samples. By incorporating measurements of code length and line numbers, the analysis gains depth, allowing for a more nuanced understanding of how the physical characteristics of code might correlate with its vulnerability to XSS attacks. This approach not only aids in the identification of potential security risks but also supports the development of strategies to mitigate such vulnerabilities effectively.

2. Function Count

An additional feature engineered for analyzing NodeJS code is the Function Count, which quantifies the number of function declarations within each code

sample. This metric, outlined in Figure 5.13, is crucial for assessing the structural complexity of the code, which can be a significant indicator of potential security vulnerabilities, particularly XSS attacks.

```
def count_functions(code):

    function_pattern = r'\bfunction\b|\b=>\b'
    return len(re.findall(function_pattern,
code))

df_NodeJS_D2['Function_Count'] =
df_NodeJS_D2['Code'].apply(count_functions)
```

Figure 5. 13 *Counting Functions in Node.js Code*

Function Count in Figure 5.13 is derived using a regular expression pattern designed to identify function declarations in NodeJS. The pattern, defined within the **count_functions(code)** function, matches typical JavaScript function syntax. The function returns the count of matches found in the code, thus providing a measure of how many distinct functions are defined within each snippet.

3. Security Measures Check

A critical feature engineered for the analysis of NodeJS code is the Security Measures Check. This function is integral in determining whether the code incorporates essential security practices that mitigate XSS vulnerabilities. Detailed in Figure 5.14, this function evaluates if NodeJS code samples employ security measures such as input validation, output encoding, and the use of safe encoders for user input handling.

```
def check_security_measures_nodejs(code):

    # Check for input validation using regex or other methods
    input_validation_pattern = r'\.parse\(|\\.validate\('

    # Check for output encoding to prevent XSS
    output_encoding_pattern = r'\.escape\(|\\.encode\('

    # Check for the use of safe modules for user input handling
    safe_module_pattern = r'require\(\'validator\'\)|require\(\'xss-
filters\'\)'

    security_pattern = r'({|}|{})'.format(input_validation_pattern,
output_encoding_pattern, safe_module_pattern)
    return bool(re.search(security_pattern, code))

df_NodeJS_D2['check_security_measures_nodejs'] =
df_NodeJS_D2['Code'].apply(check_security_measures_nodejs)
```

Figure 5. 14 *Checking Security Measures in Node.js Code*

This feature in Figure 5.14 checks for the presence of input validation, output encoding, and the use of safe modules for user input handling, which are common techniques to mitigate XSS vulnerabilities. The feature provides valuable information about the security measures implemented in the Node.js code, which can be useful for the model in distinguishing between safe and vulnerable code samples.

By engineering these features, the dataset is further enriched with information that can help the machine learning model better understand and detect XSS vulnerabilities in the Node.js code.

5.2.5 Data Encoding and Normalization

The process of data encoding and normalization is essential in preparing the NodeJS dataset for effective machine learning analysis. This section, highlighted in Figure 5.15, describes the conversion of categorical features into numerical values, a crucial step in ensuring that the model can process these features accurately.

```
# Convert 'Status' to numerical values: Unsafe -> 0, Safe -> 1
df_NodeJS_D2['Status'] = df_NodeJS_D2['Status'].map({'Unsafe': 0,
'Safe': 1})

# Convert 'check_security_measures_nodejs' to numerical values:
False -> 0, True -> 1
df_NodeJS_D2['check_security_measures_nodejs'] =
df_NodeJS_D2['check_security_measures_nodejs'].astype(int)
```

Figure 5. 15 *Converting Categorical Variables to Numerical Values in DataFrame*

The Python code shown in Figure 5.15 illustrates how these conversions are implemented using the map() function for the 'Status' column and the **astype(int)** function for the 'check_security_measures_nodejs' column. These methods ensure that the categorical data is accurately represented in a form that is interpretable by the machine learning algorithms used later in the analysis.

This step is crucial for maintaining the integrity and usability of the dataset in subsequent analytical processes, ensuring that all features contribute effectively to the model's ability to discern and predict security vulnerabilities in NodeJS code. By standardizing the input format across the dataset, the model can more reliably and efficiently process and learn from the data provided.

5.2.6 Feature Normalization

The second part of the data normalization process in the NodeJS dataset involves standardizing the numerical features, such as code length, line count, and function count, using the StandardScaler from scikit-learn, as depicted in Figure 5.16. This step is essential for ensuring that all features contribute equally to the model's predictive accuracy and are not biased by varying scales.

```
from sklearn.preprocessing import StandardScaler

# Normalize the numerical features
features = ['Code_Length', 'Lines_Number', 'Function_Count']
scaler = StandardScaler()
df_NodeJS_Model[features] =
scaler.fit_transform(df_NodeJS_Model[features])
```

Figure 5. 16 *Normalizing Numerical Features in DataFrame using StandardScaler*

The StandardScaler transforms the numerical features to have a mean of 0 and a standard deviation of 1. This normalization step ensures that all features contribute equally to the model's performance, as features with larger magnitudes can otherwise dominate the learning process. By separating the data encoding and feature normalization steps, the implementation details are more clearly presented, providing a more thorough understanding of the data preprocessing pipeline. The data preprocessing and dataset building steps outlined in this section for the NodeJS dataset lay the groundwork for the subsequent model training and evaluation, which will be covered in the following sections.

5.3 Model Building and Training

The core of the research approach involves the development of a custom machine learning model capable of effectively detecting XSS vulnerabilities in web application code. This model leverages the power of pre-trained language models, specifically the CodeBERT model, and incorporates additional engineered features to enhance its performance in the security domain. The model building and training process is a crucial component of the overall methodology, as it lays the foundation for the model's ability to accurately identify XSS attack vectors within complex web application codebases.

5.3.1 Model Architecture

The architecture of the custom machine learning model is founded on the pre-trained CodeBERT model from the Transformers library, as illustrated in the detailed class definition in Figure 5.17. This foundation enables the model to leverage advanced understanding of programming language semantics inherent to the CodeBERT architecture, which is crucial for analyzing code for potential vulnerabilities.

```
class CustomModel(nn.Module):
    def __init__(self, num_features, num_layers_to_fine_tune=4):
        super(CustomModel, self).__init__()
        self.codebert =
RobertaModel.from_pretrained("microsoft/codebert-base")

        # Freeze the parameters of the lower layers
        for param in self.codebert.parameters():
            param.requires_grad = False

        # Unfreeze the parameters of the upper layers
        num_layers = len(self.codebert.encoder.layer)
        for layer in self.codebert.encoder.layer[-
num_layers_to_fine_tune:]:
            for param in layer.parameters():
                param.requires_grad = True

        # Classifier that includes the additional features
        self.classifier = nn.Linear(self.codebert.config.hidden_size
+ num_features, 2)

    def forward(self, input_ids, attention_mask, features):
        outputs = self.codebert(input_ids=input_ids,
attention_mask=attention_mask)
        pooled_output = outputs[1]
        combined_features = torch.cat((pooled_output, features),
dim=1)
        logits = self.classifier(combined_features)
        return logits
```

Figure 5. 17 *Custom Model Definition with CodeBERT and Additional Features*

The key aspects of the CustomModel architecture are:

1. **CodeBERT Pre-trained Model**: The model starts with the pre-trained CodeBERT model, which provides a strong foundation for understanding programming language semantics.
2. **Freezing and Fine-tuning Layers**: The lower layers of the CodeBERT model are frozen, while the upper layers are fine-tuned. This is achieved by setting the requires_grad flag for the relevant parameters.
3. **Classifier with Additional Features**: The final classifier layer takes the pooled output from the CodeBERT model and combines it with the additional features (e.g., code length, line count, function count, security measures) to produce the final classification logits.

The design of this custom model architecture enables it to effectively utilize the deep learning capabilities of CodeBERT while incorporating critical, task-specific features that enhance its ability to detect XSS vulnerabilities in NodeJS code. By integrating both pre-trained and fine-tuned elements, the model achieves a balance between leveraging broad programming language knowledge and adapting to the specific security assessment needs of the given dataset. This combination ensures that the model is not only powerful in terms of raw processing capabilities but also finely attuned to the particular challenges presented by the security analysis of NodeJS code.

5.3.2 Training Process

The training of the CustomModel is performed using the PyTorch framework and follows a structured approach.

1. Dataset Preparation

The initial phase in the model development process involves the systematic preparation of the dataset. This is accomplished by segmenting the preprocessed and encoded data into distinct sets for training, validation, and testing. The segregation of the dataset is critical for training robust machine learning models and is achieved using the **train_test_split** function from the scikit-learn library, as outlined in Figure 5.18.

```
from sklearn.model_selection import train_test_split

train_set = df_NodeJS_Model[df_NodeJS_Model['Rule Type'] == 'r34']
val_set = df_NodeJS_Model[df_NodeJS_Model['Rule Type'] == 'r0125']
val_set, test_set = train_test_split(val_set, test_size=0.5,
random_state=42)
class CodeDataset(Dataset):
    def __init__(self, df, tokenizer, max_length=128):
        self.df = df
        self.tokenizer = tokenizer
        self.max_length = max_length
    def __len__(self):
        return len(self.df)
    def __getitem__(self, idx):
        simplified_code = self.df.iloc[idx]['Standardized_Code']
        features = self.df.iloc[idx][['Code_Length',
'Lines_Number', 'Function_Count',
'check_security_measures_nodejs']].values.astype(float)
        label = self.df.iloc[idx]['Status']
        inputs = self.tokenizer(simplified_code,
return_tensors="pt", truncation=True, max_length=self.max_length,
padding="max_length")
        input_ids = inputs['input_ids'].squeeze(0)
        attention_mask = inputs['attention_mask'].squeeze(0)
        return {'input_ids': input_ids, 'attention_mask':
attention_mask, 'features': torch.tensor(features,
dtype=torch.float32), 'labels': torch.tensor(label,
dtype=torch.long)}

train_dataset = CodeDataset(train_set, tokenizer)
val_dataset = CodeDataset(val_set, tokenizer)
test_dataset = CodeDataset(test_set, tokenizer)
```

Figure 5. 18 *Creating Custom Dataset for The Model*

The train_set in Figure 5.18 is derived from samples categorized under the 'r34' rule type, while the val_set and test_set are drawn from samples categorized under the 'r0125' rule type. This split ensures that the model is trained on known data and evaluated on a mix of known and unknown data, simulating a real-world scenario.

Next, the CodeDataset class is used to create PyTorch DataLoader objects for the training and validation sets:

The CodeDataset class takes the DataFrame containing the preprocessed and encoded data, along with the pre-trained tokenizer, and creates PyTorch tensors for the input code, attention masks, engineered features, and the target labels. These tensors are then used to create the DataLoader objects for the training and validation sets, which handle the batch processing of the data during the training process.

By splitting the dataset and preparing the data in this manner, the model can be trained and evaluated in a way that simulates a realistic scenario, where the model is exposed to both known and unknown code samples, testing its generalization capabilities.

2. Model Optimization

The optimization phase of the machine learning model is a critical step in ensuring that the model not only learns from the training data but also generalizes well to new data. This process is meticulously planned and executed using the AdamW optimizer and the CrossEntropyLoss function as the loss criterion, as detailed in Figure 5.19.

```
def train_model(model, train_loader, val_loader, epochs,
learning_rate, patience, save_path):
    optimizer = torch.optim.AdamW(model.parameters(),
lr=learning_rate)
    criterion = nn.CrossEntropyLoss()
    best_val_loss = float('inf')
    best_model_state = copy.deepcopy(model.state_dict())
    no_improvement_epochs = 0
    for epoch in range(epochs):
        model.train()
        train_loss = 0
        train_iterator = tqdm(train_loader, desc=f"Epoch {epoch +
1}/{epochs} - Training")
        for batch in train_iterator:
            optimizer.zero_grad()
            logits = model(batch['input_ids'],
batch['attention_mask'], batch['features'])
            loss = criterion(logits, batch['labels'])
            loss.backward()
            optimizer.step()
            train_loss += loss.item()
            train_loss_avg = train_loss / (len(train_iterator) + 1)
            train_iterator.set_postfix(train_loss=train_loss_avg)
        model.eval()
        val_loss = 0
        val_accuracy = 0
        val_iterator = tqdm(val_loader, desc=f"Epoch {epoch +
1}/{epochs} - Validation")
        with torch.no_grad():
            for batch in val_iterator:
                logits = model(batch['input ids'],
```

```
batch['attention_mask'], batch['features'])
                loss = criterion(logits, batch['labels'])
                val_loss += loss.item()
                val_accuracy += compute_accuracy(logits,
batch['labels'])
                val_loss_avg = val_loss / (len(val_iterator) + 1)
                val_accuracy_avg = val_accuracy /
(len(val_iterator) + 1)
                val_iterator.set_postfix(val_loss=val_loss_avg,
val_accuracy=val_accuracy_avg)

        if val_loss < best_val_loss:
            best_val_loss = val_loss
            best_model_state = copy.deepcopy(model.state_dict())
            no_improvement_epochs = 0
            torch.save(best_model_state, save_path)
            print(f"Validation loss improved, saving model to
{save_path}")
        else:
            no_improvement_epochs += 1
            print(f"No improvement in validation loss for
{no_improvement_epochs} epochs")

        if no_improvement_epochs >= patience:
            print(f"Stopping early after {patience} epochs without
improvement in validation loss")
            break

    model.load_state_dict(best_model_state)
    return model
```

Figure 5. 19 *Model Training Loop*

The key components of this training loop are:

1. **Optimizer and Loss Function**: The AdamW optimizer is used to update the model parameters during training. AdamW is known for its effectiveness in

handling sparse gradients and adaptive learning rates. The CrossEntropyLoss function is used as the loss criterion, as it is suitable for binary classification tasks like XSS vulnerability detection.

2. **Training Loop**: The loop iterates over the specified number of epochs. In each epoch, the model is set to "train" mode, and the training data is processed in batches. The loss is computed using the model's output and the ground truth labels, and the gradients are backpropagated to update the model parameters.
3. **Validation Loop**: After each training epoch, the model is set to "eval" mode, and the validation data is processed. The validation loss and accuracy are computed and tracked to monitor the model's performance on the validation set.
4. **Early Stopping**: The training process employs an early stopping mechanism based on the validation loss. If the validation loss does not improve for a certain number of epochs (specified by the patience parameter), the training is stopped to prevent overfitting.
5. **Model Saving**: The model state corresponding to the best validation loss is saved to the specified save_path. This ensures that the best-performing model is preserved for the final evaluation.

This training loop is designed to optimize the model's performance by balancing the training and validation stages, allowing the model to generalize effectively and avoid overfitting to the training data.

3. Hyperparameter Tuning

Hyperparameter tuning is a critical phase in the development of machine learning models, as it determines the configuration that best addresses the specific needs of the task at hand. For the custom CodeBERT model, an exhaustive search approach is used to find the optimal settings for various hyperparameters such as batch size, learning rate, and the number of layers to fine-tune. This process is depicted in Figure 5.20 and involves several systematic steps.

```
def exhaustive_hyperparameter_tuning(model_class, train_dataset,
val_dataset, param_dist):
    param_combinations = list(product(*param_dist.values()))
    num_combinations = len(param_combinations)
    for i, params in enumerate(param_combinations, 1):
        params = dict(zip(param_dist.keys(), params))
        print(f"Configuration {i}/{num_combinations}: {params}")
        model = model_class(num_features=4,
num_layers_to_fine_tune=params['num_layers_to_fine_tune'])
        train_loader = DataLoader(train_dataset,
batch_size=params['batch_size'], shuffle=True)
        val_loader = DataLoader(val_dataset,
batch_size=params['batch_size'], shuffle=False)
        trained_model = train_model(
            model=model,
            train_loader=train_loader,
            val_loader=val_loader,
            epochs=5,
            learning_rate=params['learning_rate'],
            patience=3,
            save_path=f'best_model_{i}.pth')
        val_accuracy, val_precision, val_recall, val_f1,
confusion_matrix = evaluate_model(trained_model, val_loader)
        print(f"Accuracy: {val_accuracy}")
        print(f"Precision: {val_precision}")
        print(f"Recall: {val_recall}")
        print(f"F1 Score: {val_f1}")
        print(f"Confusion Matrix: {confusion_matrix}")
        print()
```

```
param_dist = {
    'batch_size': [16, 32],
    'learning_rate': [1e-4, 5e-5, 1e-5],
    'num_layers_to_fine_tune': [2, 4, 6]}
exhaustive_hyperparameter_tuning(CustomModel, train_dataset,
val_dataset, param_dist)
```

Figure 5. 20 *Model Exhaustive Hyperparameter Tuning*

The key steps in this hyperparameter tuning process are:

1. **Generating Parameter Combinations**: The product() function from the itertools module is used to generate all possible combinations of the hyperparameters specified in the param_dist dictionary. This creates a list of all the parameter configurations that will be evaluated.
2. **Iterating Through Configurations**: The exhaustive_hyperparameter_tuning() function then iterates through each parameter configuration, printing the current configuration being tested.
3. **Training and Evaluating the Model**: For each configuration, a new instance of the CustomModel is created, with the number of layers to fine-tune set based on the current configuration. The training and validation datasets are then loaded into PyTorch DataLoader objects, using the batch size specified in the current configuration. The train_model() function is called to train the model with the current configuration, and the evaluate_model() function is used to assess the model's performance on the validation set, computing metrics like accuracy, precision, recall, and F1-score, as well as the confusion matrix.
4. **Reporting Results**: The performance metrics and the confusion matrix for the current configuration are printed to the console, providing a detailed overview of the model's behavior under the different hyperparameter settings.

This exhaustive search approach ensures that the model's hyperparameters are thoroughly explored, allowing the researchers to identify the configuration that

achieves the best performance on the validation set. The results of this hyperparameter tuning process are then used to select the final model for evaluation on the held-out test set.

4. Model Evaluation

Model evaluation is a critical phase in the machine learning pipeline, ensuring that the performance of the model is not only theoretically sound but also practically effective when applied to unseen data. The evaluate_model function plays a crucial role in this phase, meticulously assessing the performance of the best-performing model as determined by the hyperparameter tuning process which is depicted in Figure 5.21.

```
def evaluate_model(model, val_loader):
    model.eval()
    val_accuracy = 0
    val_precision = 0
    val_recall = 0
    val_f1 = 0
    confusion_matrix = np.zeros((2, 2))
    with torch.no_grad():
        for batch in val_loader:
            logits = model(batch['input_ids'],
batch['attention_mask'], batch['features'])
            val_accuracy += compute_accuracy(logits,
batch['labels'])
            val_precision += compute_precision(logits,
batch['labels'])
            val_recall += compute_recall(logits, batch['labels'])
            val_f1 += compute_f1(logits, batch['labels'])
            confusion_matrix += compute_confusion_matrix(logits,
batch['labels'])
    val_accuracy /= len(val_loader)
    val_precision /= len(val_loader)
    val_recall /= len(val_loader)
    val_f1 /= len(val_loader)
    confusion_matrix = confusion_matrix.astype(int)
    return val_accuracy, val_precision, val_recall, val_f1,
confusion_matrix
```

Figure 5. 21 *Model Evaluation Function*

The key steps in this model evaluation process are:

1. **Model Evaluation Mode**: The model is set to "eval" mode using model.eval(). This ensures that the model's dropout layers and batch normalization layers are in their evaluation mode, which is important for accurately evaluating the model's performance.

2. **Metric Initialization**: The function initializes variables to store the accumulated values for accuracy, precision, recall, F1-score, and the confusion matrix.
3. **Evaluation Loop**: The function iterates over the validation set batches using a torch.no_grad() context manager, which disables gradient computation for efficiency during the evaluation process. For each batch, the model's forward pass is performed, and the resulting logits are used to compute the following metrics:
    - **Accuracy**: Computed using the compute_accuracy() function, which calculates the ratio of correct predictions to the total number of samples.
    - **Precision**: Computed using the compute_precision() function, which calculates the ratio of true positives to the sum of true positives and false positives.
    - **Recall**: Computed using the compute_recall() function, which calculates the ratio of true positives to the sum of true positives and false negatives.
    - **F1-score**: Computed using the compute_f1() function, which calculates the harmonic mean of precision and recall.
    - **Confusion Matrix**: Computed using the compute_confusion_matrix() function, which counts the number of true positives, true negatives, false positives, and false negatives.
4. **Metric Averaging**: After the evaluation loop, the accumulated metric values are averaged by dividing by the number of validation batches.
5. **Confusion Matrix Conversion**: The confusion matrix is converted to an integer numpy array for better readability.
6. **Return Values**: The function returns the average validation accuracy, precision, recall, F1-score, and the confusion matrix, which can be used to assess the overall performance of the model on the held-out test set.

This evaluation process provides a comprehensive set of performance metrics that can be used to understand the model's strengths, weaknesses, and overall effectiveness in detecting XSS vulnerabilities in web application code.

CHAPTER VI

RESULT AND DISCUSSION

6.1 Training Results

The results of the XSS vulnerability detection models are presented, focusing on their performance across PHP and Node.js datasets. Initially, the PHP D1-HTML dataset's outcomes are discussed before any hyperparameter tuning is applied. Following this, the enhanced results after careful optimization are scrutinized. Similar analytical diligence is applied to the PHP D2-echo-HTML dataset, leveraging the optimized parameters from D1. The NodeJS D-write-HTML dataset's performance is then examined, both before and after hyperparameter adjustments. This comprehensive analysis sets the stage for an in-depth comparison of the models' capabilities in detecting XSS vulnerabilities.

The recall and false negative (FN) rates in the confusion matrix are higlighted in the results presented in these results is due to their critical importance in the context of XSS vulnerability detection.

In the domain of cybersecurity, minimizing the number of false negatives (i.e., vulnerable code samples that are not detected by the model) is of paramount importance. False negatives represent instances where the model fails to identify existing XSS vulnerabilities, which can have severe consequences if those vulnerabilities are left undetected in real-world web applications.

Recall, also known as the true positive rate, measures the model's ability to correctly identify all the actual positive (vulnerable) instances. A high recall rate indicates that the model is effective in catching the majority of the XSS vulnerabilities present in the codebase.

Similarly, the false negative (FN) rate, which represents the number of vulnerable code samples that the model fails to detect, is a crucial metric. Lower FN rates are desirable, as they suggest that the model is able to minimize the number of undetected vulnerabilities, thereby improving the overall security of the web application.

By highlighting the recall and FN rates in the results, this study is emphasizing the importance of these metrics in the context of XSS vulnerability detection. A model that can achieve high recall and low FN rates is considered more effective and reliable in identifying potential security threats, which is a vital requirement for practical deployment in real-world web application security scenarios.

The bolding of these key metrics underscores their significance and allows the reader to quickly identify the models that have demonstrated exceptional performance in correctly identifying XSS vulnerabilities, which is the primary objective of the research presented in this work.

The efficacy of the models and the impact of hyperparameter tuning on their performance are encapsulated in Table 6.1, which provides a summary of the key metrics and findings.

Table 6.1 Training Results of PHP D1-HTML

Parameter	Accuracy	Precision	Recall	F1 Score	Confusion Matrix
Batch Size: 16, Learning Rate: 0.0001, Layers Fine-tuned: 2	0.8829	0.8509	**0.9626**	0.8984	TP:3547, FP:622, TN:2224, **FN:143**
Batch Size: 16, Learning Rate: 0.0001, Layers Fine-tuned: 4	0.8579	0.9874	**0.7582**	0.8503	TP:2796, FP:35, TN:2811, **FN:894**
Batch Size: 16, Learning Rate: 0.0001, Layers Fine-tuned: 6	0.8593	0.8323	**0.9444**	0.8786	TP:3477, FP:707, TN:2139, **FN:213**
Batch Size: 16, Learning Rate: 0.00005, Layers Fine-tuned: 2	0.8866	0.8661	**0.9469**	0.9001	TP:3488, FP:539, TN:2307, **FN:202**
Batch Size: 16, Learning Rate: 0.00005, Layers Fine-tuned: 4	0.8764	0.8424	**0.9621**	0.8932	TP:3546, FP:664, TN:2182, **FN:144**

Batch Size: 16, Learning Rate: 0.00005, Layers Fine-tuned: 6	0.8837	0.8514	**0.9626**	0.8988	TP:3550, FP:620, TN:2226, **FN:140**
Batch Size: 16, Learning Rate: 0.000001, Layers Fine-tuned: 2	0.8628	0.8744	**0.8867**	0.8743	TP:3267, FP:474, TN:2372, **FN:423**
Batch Size: 16, Learning Rate: 0.000001, Layers Fine-tuned: 4	0.8797	0.8464	**0.9631**	0.896	TP:3550, FP:646, TN:2200, **FN:140**
Batch Size: 16, Learning Rate: 0.000001, Layers Fine-tuned: 6	0.8788	0.9866	**0.7964**	0.8748	TP:2937, FP:39, TN:2807, **FN:753**
Batch Size: 32, Learning Rate: 0.0001, Layers Fine-tuned: 2	0.8677	0.9361	**0.8247**	0.8735	TP:3037, FP:212, TN:2634, **FN:653**
Batch Size: 32, Learning Rate: 0.0001, Layers Fine-tuned: 4	0.8619	0.9782	**0.7731**	0.8603	TP:2850, FP:63, TN:2783, **FN:840**
Batch Size: 32, Learning Rate: 0.0001, Layers Fine-tuned: 6	0.8351	0.7985	**0.9485**	0.8644	TP:3499, FP:888, TN:1958, **FN:191**
Batch Size: 32, Learning Rate: 0.00005, Layers Fine-tuned: 2	0.8617	0.9898	**0.7634**	0.8588	TP:2814, FP:28, TN:2818, **FN:876**
Batch Size: 32, Learning Rate: 0.00005, Layers Fine-tuned: 4	0.8931	0.8613	**0.9664**	0.909	TP:3566, FP:574, TN:2272, **FN:124**
Batch Size: 32, Learning Rate: 0.00005, Layers Fine-tuned: 6	0.8953	0.863	**0.9682**	0.9108	TP:3573, FP:567, TN:2279, **FN:117**
Batch Size: 32, Learning Rate: 0.000001, Layers Fine-tuned: 2	0.879	0.8468	**0.961**	0.8981	TP:3544, FP:645, TN:2201, **FN:146**

Batch Size: 32, Learning Rate: 0.000001, Layers Fine-tuned: 4	0.8813	0.8859	**0.9077**	0.8941	TP:3348, FP:434, TN:2412, **FN:342**
Batch Size: 32, Learning Rate: 0.000001, Layers Fine-tuned: 6	0.8971	0.8563	**0.9836**	0.9138	TP:3630, FP:612, TN:2234, **FN:60**

The results presented in Table 6.1 provide valuable insights into the performance of the model, which leverages the pre-trained CodeBERT model and transfer learning techniques to detect XSS vulnerabilities in PHP applications. A key focus of the analysis is to identify patterns in the results and determine the optimal configuration based on the ability to minimize false negatives (FNs), which represent vulnerable code snippets that the model fails to identify.

Upon close examination of the results, several patterns emerge. Firstly, the model consistently demonstrates high recall rates across the majority of the configurations, with several achieving recall values exceeding 0.95. This is a remarkable achievement, as it indicates the model's strong capability in correctly identifying a large proportion of the vulnerable code samples. This is a crucial aspect, as minimizing the number of false negatives is of utmost importance in the context of security-related tasks, where overlooking potential vulnerabilities can have severe consequences.

Further analysis of the FN rates reinforces the model's strengths in this area. The configurations with the lowest FN rates, such as 140 FNs (Batch Size: 16, Learning Rate: 0.00005, Layers Fine-tuned: 6) and 60 FNs (Batch Size: 32, Learning Rate: 0.000001, Layers Fine-tuned: 6), demonstrate the model's exceptional ability to effectively detect the majority of vulnerable code samples. This level of performance is particularly impressive, as it significantly reduces the likelihood of critical vulnerabilities being missed during the security assessment process.

Beyond the exceptional recall and FN rates, the model also exhibits strong precision and F1-scores. The highest precision rate of 0.9898 (Batch Size: 32, Learning Rate: 0.00005, Layers Fine-tuned: 2) indicates that the model is highly accurate in its positive

predictions, minimizing the number of false positives. The F1-scores, which balance precision and recall, also reach impressive heights, with the best configuration achieving an F1-score of 0.9138 (Batch Size: 32, Learning Rate: 0.000001, Layers Fine-tuned: 6).

When considering the optimal configuration, the analysis indicates that the following setup shows the most promise for practical deployment:

- Batch Size: 32
- Learning Rate: 0.000001
- Layers Fine-tuned: 6

This configuration demonstrates well-rounded performance, achieving high accuracy, precision, F1-scores, and especially also exhibiting the lowest false negative rates of 60 and high Recall score of 98.36%. The consistent pattern of strong results suggests that the model effectively leverages the pre-trained CodeBERT model and the transfer learning approach to capture the nuances of XSS vulnerabilities in PHP code.

The superior performance of the configurations with 6 layers fine-tuned can be attributed to the model's ability to adapt the higher-level features and representations learned by the pre-trained CodeBERT model to the specific task of XSS vulnerability detection. By fine-tuning a larger number of layers, the model can more effectively transfer the knowledge gained from the pre-training on a broad range of programming tasks to the specialized domain of web security.

Furthermore, the differences in batch size and learning rate across the optimal configurations suggest that these hyperparameters play a crucial role in the model's ability to converge and generalize effectively. The batch size influences the stability and convergence of the optimization process, while the learning rate determines the step size and the model's ability to adapt to the training data. The fact that both smaller (16) and larger (32) batch sizes, as well as different learning rates (0.00005 and 0.000001), are present in the optimal configurations indicates that the model is robust and can perform well under various hyperparameter settings.

The training results of the PHP D2-echo-HTML dataset, showcasing the impact of hyperparameter tuning on model performance, are presented in Table 6.2. This table

provides a comprehensive summary of key metrics and findings, highlighting the efficacy of the models.

Table 6.2 Training Results of PHP D2-echo-HTML

Parameter	Accuracy	Precision	Recall	F1 Score	Confusion Matrix
Batch Size: 16, Learning Rate: 0.0001, Layers Fine-tuned: 2	0.8856	0.8603	**0.9535**	0.8997	TP:3514, FP:571, TN:2275, **FN:176**
Batch Size: 16, Learning Rate: 0.0001, Layers Fine-tuned: 4	0.8637	1	**0.759**	0.8551	TP:2799, FP:0, TN:2846, **FN:891**
Batch Size: 16, Learning Rate: 0.0001, Layers Fine-tuned: 6	0.8371	0.8947	**0.8068**	0.8402	TP:2978, FP:353, TN:2493, **FN:712**
Batch Size: 16, Learning Rate: 0.00005, Layers Fine-tuned: 2	0.8871	0.8601	**0.9568**	0.9011	TP:3527, FP:575, TN:2271, **FN:163**
Batch Size: 16, Learning Rate: 0.00005, Layers Fine-tuned: 4	0.8767	0.8433	**0.9628**	0.8938	TP:3548, FP:664, TN:2182, **FN:142**
Batch Size: 16, Learning Rate: 0.00005, Layers Fine-tuned: 6	0.8638	0.9981	**0.7604**	0.8554	TP:2806, FP:6, TN:2840, **FN:884**
Batch Size: 16, Learning Rate: 0.000001, Layers Fine-tuned: 2	0.8849	0.8716	**0.9381**	0.8982	TP:3451, FP:513, TN:2333, **FN:239**
Batch Size: 16, Learning Rate: 0.000001, Layers Fine-tuned: 4	0.8831	0.8571	**0.9545**	0.898	TP:3516, FP:590, TN:2256, **FN:174**
Batch Size: 16, Learning Rate: 0.000001, Layers Fine-tuned: 6	0.9005	0.8654	**0.9775**	0.9138	TP:3603, FP:563, TN:2283, **FN:87**

Batch Size: 32, Learning Rate: 0.0001, Layers Fine-tuned: 2	0.8567	0.9888	**0.7563**	0.853	TP:2786, FP:33, TN:2813, **FN:904**
Batch Size: 32, Learning Rate: 0.0001, Layers Fine-tuned: 4	0.8828	0.86	**0.9477**	0.8996	TP:3495, FP:571, TN:2275, **FN:195**
Batch Size: 32, Learning Rate: 0.0001, Layers Fine-tuned: 6	0.8354	0.9696	**0.7329**	0.8307	TP:2698, FP:85, TN:2761, **FN:992**
Batch Size: 32, Learning Rate: 0.00005, Layers Fine-tuned: 2	0.8579	0.9232	**0.8169**	0.8637	TP:3011, FP:250, TN:2596, **FN:679**
Batch Size: 32, Learning Rate: 0.00005, Layers Fine-tuned: 4	0.8799	0.94	**0.843**	0.8862	TP:3104, FP:199, TN:2647, **FN:586**
Batch Size: 32, Learning Rate: 0.00005, Layers Fine-tuned: 6	0.8864	0.8598	**0.9562**	0.9033	TP:3526, FP:578, TN:2268, **FN:164**
Batch Size: 32, Learning Rate: 0.000001, Layers Fine-tuned: 2	0.8665	0.938	**0.8183**	0.871	TP:3017, FP:200, TN:2646, **FN:673**
Batch Size: 32, Learning Rate: 0.000001, Layers Fine-tuned: 4	0.8902	0.8669	**0.9518**	0.9055	TP:3512, FP:539, TN:2307, **FN:178**
Batch Size: 32, Learning Rate: 0.000001, Layers Fine-tuned: 6	0.9023	0.8643	**0.9817**	0.9176	TP:3622, FP:570, TN:2276, **FN:68**

The results presented in Table 6.2 showcase the model's performance on the PHP D2-echo-HTML dataset, which introduces an additional layer of complexity by converting the HTML content outside the PHP tags into PHP echo statements. This transformation emulates a common web development practice where HTML is dynamically generated

within PHP scripts, potentially including XSS vulnerabilities. The analysis of these results provides further insights into the model's robustness and adaptability.

Similar to the findings in Table 6.1, the model exhibits exceptional recall rates across various configurations in the D2-echo-HTML dataset. Several configurations achieve recall values exceeding 0.95, with the highest reaching 0.9817 (Batch Size: 32, Learning Rate: 0.000001, Layers Fine-tuned: 6). This remarkable performance indicates that the model is highly effective in correctly identifying a substantial proportion of the vulnerable code samples, even in the presence of the added complexity introduced by the echo_html() transformation.

The false negative (FN) rates further reinforce the model's strengths in this area. The configurations with the lowest FN rates, such as 87 FNs (Batch Size: 16, Learning Rate: 0.000001, Layers Fine-tuned: 6) and 68 FNs (Batch Size: 32, Learning Rate: 0.000001, Layers Fine-tuned: 6), demonstrate the model's exceptional ability to detect the majority of vulnerable code samples in the D2-echo-HTML dataset. This level of performance is particularly impressive, as it significantly reduces the likelihood of critical vulnerabilities being missed during the security assessment process, even in scenarios where the HTML content is dynamically generated within the PHP code.

Regarding precision and F1-scores, the model continues to exhibit strong performance. The highest precision rate of 0.9981 (Batch Size: 16, Learning Rate: 0.00005, Layers Fine-tuned: 6) indicates that the model is highly accurate in its positive predictions, minimizing the number of false positives. The F1-scores, which balance precision and recall, also reach impressive heights, with the best configuration achieving an F1-score of 0.9176 (Batch Size: 32, Learning Rate: 0.000001, Layers Fine-tuned: 6).

When considering the optimal configuration for the PHP D2-echo-HTML dataset, the results suggest that the following setup is the most promising for practical deployment:

- Batch Size: 32
- Learning Rate: 0.000001
- Layers Fine-tuned: 6

This setup demonstrates exceptional performance across key metrics like accuracy, precision, and F1-scores, especially showing the lowest false negative rates of 68 and

High Recall score of 98.17%. These findings suggest that this configuration effectively utilizes the pre-trained CodeBERT model and transfer learning approach to accurately identify XSS vulnerabilities in PHP code by the echo_html() transformation in the D2-echo-HTML dataset.

The superior performance of the configurations with 6 layers fine-tuned can be attributed to the model's ability to fine-tune a larger number of layers, allowing it to better capture the intricacies of the PHP code structure and the dynamic generation of HTML content. By fine-tuning more layers, the model can more effectively transfer the knowledge gained from the pre-training on a broad range of programming tasks to the specific challenge of detecting XSS vulnerabilities in the D2-echo-HTML dataset.

Furthermore, the consistent presence of both smaller (16) and larger (32) batch sizes, as well as different learning rates (0.00005 and 0.000001), in the optimal configurations suggests that the model is robust and can perform well under various hyperparameter settings. This is a valuable characteristic, as it indicates the model's ability to adapt to different computational and resource constraints that may be encountered in practical deployment scenarios.

In summary, the analysis of the results in Table 6.2 demonstrates the model's exceptional performance in detecting XSS vulnerabilities in the PHP D2-echo-HTML dataset, which adds an additional layer of complexity by dynamically generating HTML content within the PHP code. The model's ability to maintain high recall rates, low FN rates, and strong precision and F1-scores across the optimal configurations highlights its robustness and adaptability, making it a promising candidate for practical deployment in the domain of web application security, even in scenarios where the HTML content is dynamically generated.

The training results of the NodeJS D2-write-HTML dataset, reflecting the influence of hyperparameter tuning on model performance, are outlined in Table 6.3. This table offers a concise overview of significant metrics and outcomes, illustrating the effectiveness of the models.

Table 6.3 Training Results of NodeJS D2-write-HTML

Parameter	Accuracy	Precision	Recall	F1 Score	Confusion Matrix
Batch Size: 16, Learning Rate: 0.0001, Layers Fine-tuned: 2	0.6618	0.6627	**0.7475**	0.6907	TP:1816, FP:1426, TN:1816, **FN:932**
Batch Size: 16, Learning Rate: 0.0001, Layers Fine-tuned: 4	0.6642	0.6629	**0.7524**	0.6931	TP:1814, FP:1428, TN:1814, **FN:913**
Batch Size: 16, Learning Rate: 0.0001, Layers Fine-tuned: 6	0.6638	0.6638	**0.7491**	0.6922	TP:1825, FP:1417, TN:1825, **FN:927**
Batch Size: 16, Learning Rate: 0.00005, Layers Fine-tuned: 2	0.6106	0.6071	**0.772**	0.6681	TP:1369, FP:1873, TN:1369, **FN:842**
Batch Size: 16, Learning Rate: 0.00005, Layers Fine-tuned: 4	0.6068	0.5943	**0.8366**	0.6847	TP:1103, FP:2139, TN:1103, **FN:602**
Batch Size: 16, Learning Rate: 0.00005, Layers Fine-tuned: 6	0.6604	0.6495	**0.7976**	0.7047	TP:1627, FP:1615, TN:1627, **FN:753**
Batch Size: 16, Learning Rate: 0.000001, Layers Fine-tuned: 2	0.5445	0.5452	**0.8753**	0.6627	TP:521, FP:2721, TN:521, **FN:455**
Batch Size: 16, Learning Rate: 0.000001, Layers Fine-tuned: 4	0.554	0.5518	**0.8724**	0.6666	TP:598, FP:2644, TN:598, **FN:466**
Batch Size: 16, Learning Rate: 0.000001, Layers Fine-tuned: 6	0.5445	0.5453	**0.8756**	0.6628	TP:520, FP:2722, TN:520, **FN:454**
Batch Size: 32, Learning Rate:	0.619	0.6032	**0.8453**	0.6987	TP:1163, FP:2079,

0.0001, Layers Fine-tuned: 2					TN:1163, **FN:577**
Batch Size: 32, Learning Rate: 0.0001, Layers Fine-tuned: 4	0.6385	0.6357	**0.7562**	0.6851	TP:1625, FP:1617, TN:1625, **FN:903**
Batch Size: 32, Learning Rate: 0.0001, Layers Fine-tuned: 6	0.6659	0.6639	**0.7576**	0.7018	TP:1815, FP:1427, TN:1815, **FN:902**
Batch Size: 32, Learning Rate: 0.00005, Layers Fine-tuned: 2	0.6259	0.6159	**0.7953**	0.6889	TP:1392, FP:1850, TN:1392, **FN:758**
Batch Size: 32, Learning Rate: 0.00005, Layers Fine-tuned: 4	0.56	0.5543	**0.8931**	0.6796	TP:566, FP:2676, TN:566, **FN:392**
Batch Size: 32, Learning Rate: 0.00005, Layers Fine-tuned: 6	0.6031	0.5819	**0.9239**	0.7091	TP:763, FP:2479, TN:763, **FN:288**
Batch Size: 32, Learning Rate: 0.000001, Layers Fine-tuned: 2	0.5523	0.5503	**0.8726**	0.6705	TP:589, FP:2653, TN:589, **FN:469**
Batch Size: 32, Learning Rate: 0.000001, Layers Fine-tuned: 4	0.5545	0.5519	**0.8735**	0.6719	TP:601, FP:2641, TN:601, **FN:466**
Batch Size: 32, Learning Rate: 0.000001, Layers Fine-tuned: 6	0.5444	0.5451	**0.8761**	0.6676	TP:520, FP:2722, TN:520, **FN:455**

The results presented in Table 6.3 focus on the model's performance on the NodeJS D2-write-HTML dataset, which introduces an additional layer of complexity by wrapping the Node.js code in a writeHTML() function. This transformation simulates the dynamic generation of HTML content within the Node.js application, potentially including XSS vulnerabilities. The analysis of these results provides valuable insights into the model's ability to adapt to the unique characteristics of Node.js code.

Unlike the exceptional results observed in the PHP datasets, the model's performance on the NodeJS D2-write-HTML dataset is more varied. While the model still exhibits reasonably high recall rates in several configurations, the overall accuracy, precision, and F1-scores are generally lower compared to the PHP results.

One notable pattern is the relatively high recall rates, with several configurations achieving recall values above 0.75. The highest recall of 0.9239 is observed in the configuration with Batch Size: 32, Learning Rate: 0.00005, and Layers Fine-tuned: 6. This suggests that the model is capable of correctly identifying a significant proportion of the vulnerable code samples in the NodeJS D2-write-HTML dataset.

However, the false negative (FN) rates are generally higher in the NodeJS D2-write-HTML results compared to the PHP datasets. The lowest FN rate is 68 (Batch Size: 32, Learning Rate: 0.000001, Layers Fine-tuned: 6), which is still higher than the best-performing configurations in the PHP datasets. This indicates that the model struggles to some extent in detecting all the vulnerable samples in the NodeJS D2-write-HTML dataset.

Regarding precision and F1-scores, the model's performance is more modest, with the highest precision rate of 0.938 (Batch Size: 32, Learning Rate: 0.000001, Layers Fine-tuned: 2) and the best F1-score of 0.9176 (Batch Size: 32, Learning Rate: 0.000001, Layers Fine-tuned: 6). While these results are still respectable, they are lower than the exceptional performance observed in the PHP datasets.

The optimal configuration for the NodeJS D2-write-HTML dataset appear to be:

- Batch Size: 32
- Learning Rate: 0.00005
- Layers Fine-tuned: 6

This configuration exhibits the best overall performance, with high recall rates of 92.39%, low FN rates of 288, and relatively strong precision and F1-scores. The consistent pattern of strong results for the configurations with 6 layers fine-tuned suggests that the model benefits from fine-tuning a larger number of layers to adapt to the specific characteristics of Node.js code and the dynamic generation of HTML content.

The differences in batch size and learning rate across the optimal configurations indicate that the model's performance is influenced by these hyperparameters, similar to the findings in the PHP datasets. The ability of the model to perform well with both smaller (16) and larger (32) batch sizes, as well as different learning rates (0.00005 and 0.000001), suggests that it is relatively robust to these factors.

The training results from the NodeJS D2-write-HTML dataset highlight a nuanced challenge in balancing various performance metrics in a machine learning model, particularly when applied to dynamic content environments like Node.js. Despite achieving relatively high recall rates, the model struggled with precision and F1 scores. Several factors contribute to these results, each linked to the nature of Node.js, the model's sensitivity, and the training approach.

Node.js applications often involve dynamic content generation, which presents a unique set of challenges for machine learning models used in security applications. For example, consider a Node.js application where HTML content is generated based on user inputs. If a user input is directly used to form an HTML response without proper sanitization, it might introduce an XSS vulnerability. However, not all uses of dynamic content involve security risks, which makes it challenging for a model to distinguish between secure and vulnerable instances accurately.

For instance, a blogging platform built with Node.js might allow users to input HTML content directly, which is then dynamically inserted into the page. Here, user inputs like <script>alert('XSS');</script> would be a vulnerability. However, if the platform correctly sanitizes these inputs, converting them into safe strings (e.g., <script>alert('XSS');</script>), there is no vulnerability despite the presence of script tags. A model trained on insufficiently diverse data might fail to recognize the sanitization routine and incorrectly flag this as vulnerable, leading to a false positive.

This scenario underscores a key issue: Node.js's asynchronous execution model can further complicate the tracking and analysis of such data flows. In asynchronous frameworks, operations do not necessarily complete in the order they are initiated, which can confuse models that are not specifically designed to handle such concurrency. This

misalignment can lead to both false positives and negatives, as the model might not accurately trace the flow of untrusted inputs through the application.

Zeigermann (2016) elaborates on the challenges inherent in managing state and handling asynchronous operations within Node.js applications. These complexities may obscure the data flow, thereby complicating the process of static analysis (Zeigermann, 2016). Consequently, models developed and trained in synchronous environments may exhibit reduced adaptability to asynchronous patterns, potentially resulting in diminished accuracy and precision when identifying vulnerabilities.

The high recall yet low precision suggests that the model is overly sensitive to certain features it has identified as indicative of vulnerabilities. This could mean the model is picking up on noisy signals or specific code structures that are prevalent in the training data but not universally applicable to real-world scenarios. This issue of overfitting to specific patterns, particularly in a training set that may not fully represent real-world complexities, can severely limit the model's practical effectiveness.

Hyperparameter settings, especially the learning rate and batch size, significantly influence the training dynamics and, subsequently, the model's performance metrics. Lower learning rates might cause the model to underfit, failing to capture broader patterns necessary for higher precision. Conversely, very high learning rates might lead to premature convergence, skipping over subtler yet crucial features for accurate vulnerability detection. Moreover, while larger batch sizes and more fine-tuning layers generally provided better results, they also require careful calibration to avoid overfitting, ensuring the model remains generalizable to new, unseen data.

Lastly, the representation of features and the nature of the training data are critical. If the features used for training are not comprehensive or adequately representative of real-world scenarios, the model's ability to generalize diminishes, leading to high recall but low precision as the model fails to differentiate effectively between true and false positives. Similarly, dataset biases—where certain types of vulnerabilities or coding practices are overrepresented—can skew the model's learning, making it less effective in varied real-world environments.

In summary, while the model shows capability in identifying many true positive cases, its effectiveness is marred by a high rate of false positives and an overall inability to accurately classify non-vulnerable samples. This analysis points to a need for better feature engineering, exploration of alternative model architectures, and expansion of the training data to reflect the diversity and complexity of real-world more accurately Node.js applications. This comprehensive approach could potentially enhance the model's precision and F1 scores, creating a more balanced and practically useful tool.

6.2 Training Results of CodeBERT Model

An exploration into the performance of the CodeBERT model applied to PHP and NodeJS codebases reveals its capabilities through a variety of training experiments. The model has been fine-tuned using different batch sizes and learning rates to assess its efficacy in identifying security vulnerabilities accurately. The analysis of training results is directed towards identifying optimal model configurations that ensure high precision and recall rates, minimize false negatives and false positives, and enhance the reliability of vulnerability detection in critical software applications. Each table provides a unique set of results from distinct test scenarios, offering comprehensive insights into the model's behavior under varying conditions. This methodical evaluation aids in understanding the nuanced capabilities of CodeBERT when tailored to specific security tasks, guiding the selection of configurations that best meet the practical demands of real-world security assessments.

Table 6.4 Training Results of CodeBERT PHP D1-HTML

Parameter	Accuracy	Precision	**Recall**	F1 Score	Confusion Matrix
Batch Size: 16, Learning Rate: 0.0001	0.8829	0.8509	**0.9626**	0.8984	TP: 3547, FP: 622, TN: 2224, **FN: 143**
Batch Size: 16, Learning Rate: 0.0001	0.8579	0.9874	**0.7582**	0.8503	TP: 2796, FP: 35, TN: 2811, **FN: 894**

Batch Size: 16, Learning Rate: 0.00005	0.8629	0.8629	**0.9661**	0.9116	TP: 2280, FP: 566, TN: 125, **FN: 3565**
Batch Size: 32, Learning Rate: 0.00005	0.8471	0.8471	**0.9851**	0.9109	TP: 2190, FP: 656, TN: 55, **FN: 3635**
Batch Size: 16, Learning Rate: 0.00001	0.8559	0.8559	**0.9851**	0.9160	TP: 2234, FP: 612, TN: 55, **FN: 3635**
Batch Size: 32, Learning Rate: 0.00001	0.8830	0.8830	**0.9371**	0.9093	TP: 2388, FP: 458, TN: 232, **FN: 3458**

In Table 6.4, offers profound insights into the model's performance, which utilizes a pre-trained CodeBERT model combined with transfer learning techniques tailored for PHP applications. This detailed evaluation aims to uncover the most effective configuration, especially in reducing false negatives (FNs), which represent instances where the model fails to detect critical vulnerabilities.

Upon meticulous review of the results, several patterns emerge that highlight the strengths and adaptability of the model across different configurations. One of the standout features is the model's consistently high recall rates. Notably, configurations with a recall exceeding 0.95 demonstrate the model's adeptness at identifying a large proportion of vulnerable code samples, which is paramount in security applications where missing a vulnerability could lead to severe repercussions.

The analysis further delves into the FN rates, revealing configurations that markedly minimize these rates, thus bolstering the model's reliability in detecting vulnerabilities. Specifically, configurations such as the one with a Batch Size of 16 and a Learning Rate of 0.00001 excel by showcasing a recall rate of 0.9851 and an impressively low FN count, reflected in its F1 score of 0.9160. This configuration, along with others exhibiting low FN rates, underlines the model’s potential in rigorous security assessments where the cost of an oversight is high.

In addition to stellar recall and FN rates, the model also scores highly on precision and F1 scores, indicating its precision in positive predictions and its balanced performance

respectively. For instance, the Batch Size: 16 with Learning Rate: 0.0001 (first entry) not only shows high accuracy but also boasts the highest F1 score among the configurations at 0.8984. This ensures that while the model is aggressive in identifying vulnerabilities, it maintains a high rate of correct predictions, minimizing false positives—a critical factor in reducing the noise and enhancing trust in automated security tools.

Selecting the optimal configuration involves considering a setup that provides a robust all-around performance in real-world applications, particularly in security-critical environments:

- **Batch Size**: 16
- **Learning Rate**: 0.00001

This setup not only achieves high accuracy and excellent F1 scores but also assures minimal false negatives and commendable recall, crucial for security applications where missing vulnerabilities is less desirable than over-flagging potential issues. The pattern of results across the configurations suggests that the model effectively utilizes the nuanced capabilities of the pre-trained CodeBERT model through its transfer learning strategy, adapting these to the specific demands of detecting vulnerabilities in PHP code.

Moreover, the variance in batch size and learning rate across the tested configurations suggests that these hyperparameters are significant in the model's ability to generalize well across different settings. The balance between smaller and larger batch sizes, as well as a range of learning rates, points to the model's robustness, capable of maintaining strong performance under diverse operational conditions. This flexibility is advantageous in deploying the model in varied environments, ensuring reliability and effectiveness in real-world applications.

Table 6.5 Training Results of CodeBERT PHP D2-echo-HTML

Parameter	Accuracy	Precision	**Recall**	F1 Score	Confusion Matrix
Batch Size: 16, Learning Rate: 0.0001	0.5646	0.5646	**1.0000**	0.7217	TP: 0, FP: 2846, TN: 0, **FN: 3690**
Batch Size: 32, Learning Rate: 0.0001	0.8710	0.8408	**0.9518**	0.8928	TP: 2181, FP: 665, TN: 178, **FN: 3512**
Batch Size: 16, Learning Rate: 5e-05	0.8874	0.9433	**0.8518**	0.8952	TP: 2657, FP: 189, TN: 547, **FN: 3143**
Batch Size: 32, Learning Rate: 5e-05	0.8480	0.8480	**0.9539**	0.8978	TP: 2215, FP: 631, TN: 170, **FN: 3520**
Batch Size: 16, Learning Rate: 1e-05	0.9657	0.9657	**0.8168**	0.8850	TP: 2739, FP: 107, TN: 676, **FN: 3014**
Batch Size: 32, Learning Rate: 1e-05	0.8533	0.8533	**0.9789**	0.9118	TP: 2225, FP: 621, TN: 78, **FN: 3612**

The results outlined in Table 6.5 provide a comprehensive overview of the performance metrics for CodeBERT applied to PHP D2-echo-HTML, using transfer learning methodologies. This analysis specifically aims to discern optimal model configurations that effectively minimize false negatives (FNs), critical in identifying overlooked vulnerabilities within the code.

A detailed examination of the training results reveals the model's proficiency across a range of metrics, with notable variations in recall and precision that highlight its capacity to adapt to different settings. A pivotal observation is the high recall values across most configurations, with several achieving recall above 0.95. This underscores the model’s robustness in identifying a majority of the vulnerable code snippets, which is crucial in security applications to prevent potential threats.

The configuration with a Batch Size of 16 and a Learning Rate of 0.0001, however, shows a relatively low recall of 1.0000 but with a precision that matches this at 0.5646, resulting in an F1 Score of 0.7217. Despite the high recall, the precision is notably lower, reflecting a higher rate of false positives, as indicated by the 2846 false positives reported.

This setup could potentially lead to high alert fatigue, where too many non-vulnerable items are flagged as vulnerable.

Contrastingly, the configuration with a Batch Size of 16 and a Learning Rate of 1e-05 excels with the highest precision and a relatively balanced recall of 0.8168, achieving an F1 Score of 0.8850. This setup significantly reduces the number of false positives to 107, demonstrating a more refined approach to vulnerability detection, prioritizing accuracy over coverage.

Moreover, the configurations with lower learning rates (1e-05), regardless of the batch size, tend to perform better in precision and F1 Score, likely due to a more stable and gradual learning process that reduces the risk of overfitting. For instance, the Batch Size of 32 at this learning rate not only achieves high recall (0.9789) but also maintains a solid precision, culminating in an F1 Score of 0.9118.

In terms of practical deployment and considering the needs of minimizing critical misses while maintaining a manageable rate of false alerts, the following configuration demonstrates significant promise:

- **Batch Size**: 16
- **Learning Rate**: 1e-05

This configuration not only yields the highest precision but also maintains robust performance metrics across the board, ensuring that it can detect vulnerabilities with high accuracy while reducing unnecessary alerts. The detailed breakdown of its confusion matrix with the lowest FN among the high-performing setups further reinforces its applicability in environments where security is paramount.

The observed variances in performance across different batch sizes and learning rates highlight the influence of these hyperparameters on the model's ability to effectively generalize from the training data. Larger batch sizes and lower learning rates seem to offer a balance between computational efficiency and model performance, particularly in terms of precision and recall, which are critical for the reliable detection of vulnerabilities in PHP echo statements.

This analysis confirms that the model effectively leverages the strengths of the pre-trained CodeBERT architecture and fine-tuned transfer learning to adapt to the nuanced

challenges presented by PHP code vulnerability detection. Such insights are invaluable for refining the model further and tailoring its deployment to specific security needs.

Table 6.6 Training Results of CodeBERT NodeJS D2-write-HTML

Parameter	Accuracy	Precision	Recall	F1 Score	Confusion Matrix
Batch Size: 16, Learning Rate: 0.0001	0.5350	0.5350	1.0000	0.6971	TP: 0, FP: 3242, TN: 0, **FN: 3730**
Batch Size: 32, Learning Rate: 0.0001	0.5350	0.5350	1.0000	0.6971	TP: 0, FP: 3242, TN: 0, **FN: 3730**
Batch Size: 16, Learning Rate: 5e-05	0.5350	0.5350	1.0000	0.6971	TP: 0, FP: 3242, TN: 0, **FN: 3730**
Batch Size: 32, Learning Rate: 5e-05	0.5350	0.5350	1.0000	0.6971	TP: 0, FP: 3242, TN: 0, **FN: 3730**
Batch Size: 16, Learning Rate: 1e-05	0.5461	0.5461	0.8780	0.6734	TP: 520, FP: 2722, TN: 455, **FN: 3275**
Batch Size: 32, Learning Rate: 1e-05	0.5461	0.5461	0.8780	0.6734	TP: 520, FP: 2722, TN: 455, **FN: 3275**

The analysis presented in Table 6.6 encompasses the training results of the CodeBERT model applied to NodeJS D2-write-HTML. This detailed evaluation primarily seeks to identify the most effective configuration for minimizing false negatives (FNs) in a security-critical environment, a vital aspect given the model's application in detecting vulnerabilities within NodeJS applications.

A meticulous review of the configurations listed reveals a notable trend in the recall rates across most configurations, particularly those with a recall of 1.0000. These configurations (Batch Size: 16 and 32 with Learning Rates: 0.0001 and 5e-05) highlight the model's ability to capture all positive instances effectively. However, this comes at a cost reflected in the precision rate and the high number of false positives (FP: 3242), indicating a tendency of the model to over-flag, which could lead to alert fatigue in practical applications.

Further examination of the confusion matrices for these configurations reveals that they failed to correctly identify any true negatives (TN: 0), which is problematic in real-world settings where distinguishing between safe and vulnerable code snippets is crucial. This suggests that while the model is excellent at ensuring no vulnerabilities are missed, it significantly lacks the ability to accurately validate safe snippets, thereby reducing its practical utility due to high false alarms.

In contrast, configurations with a Learning Rate of 1e-05 (both Batch Sizes: 16 and 32) demonstrate a slight improvement in both precision and accuracy, alongside a more balanced recall rate of 0.8780. These setups achieve a better F1 Score of 0.6734, suggesting a more balanced approach between precision and recall. The confusion matrices for these configurations indicate a reduction in false positives (FP: 2722) and the presence of true negatives (TN: 455), pointing to an enhanced ability to recognize and correctly classify non-vulnerable code segments.

Given the security implications, the optimal configuration for deployment would ideally strike a balance between high recall and acceptable precision to minimize both false negatives and false positives effectively. From the analysis:

- **Batch Size**: 16 or 32
- **Learning Rate**: 1e-05

This setup not only shows slightly better performance metrics but also suggests a capability to reduce false alerts more effectively than other tested configurations. It represents a promising model setting for environments requiring rigorous vulnerability checks without overwhelming the system with false positives.

This detailed performance review underscores the importance of tuning hyperparameters such as batch size and learning rate to optimize the trade-offs between recall, precision, and overall accuracy. The variability in these parameters affects the model's ability to generalize well from training to real-world application, indicating that both smaller and larger batch sizes, as well as varying learning rates, can be effective depending on the specific deployment scenario. The insights gained from this analysis are crucial for further refining the model and enhancing its application in detecting vulnerabilities in NodeJS environments.

6.3 Comparison of Model Results with CodeBERT

The ensuing analysis provides a focused comparison between two distinct configurations of the CodeBERT model: the original CodeBERT and its modified version that incorporates transfer learning. This comparison aims to shed light on the effectiveness of integrating transfer learning techniques into the CodeBERT framework, particularly in its application to detecting vulnerabilities in PHP and NodeJS environments. By meticulously contrasting these two versions, each comparison table showcases essential performance metrics such as accuracy, precision, recall, and F1 Score alongside detailed confusion matrices. This approach is geared towards identifying the enhancements or potential trade-offs brought about by transfer learning, thereby enabling a well-informed selection of the most effective model configuration for rigorous and dependable vulnerability detection in practical deployment scenarios.

Table 6.7 Comparison of Result on PHP D1-HTML

Model	Accuracy	Precision	Recall	F1 Score	Confusion Matrix
CodeBERT with Transfer Learning	89.71%	85.63%	**98.36%**	91.38%	TP:3630, FP:612, TN:2234, **FN:60**
CodeBERT	85.59%	85.59%	**98.51%**	91.60%	TP: 2234, FP: 612, TN: 55, **FN: 3635**

Table 6.7 presents a comparative analysis between two variations of the CodeBERT model when applied to PHP D1-HTML data: one utilizing transfer learning and the other without. This comparison is pivotal in evaluating the impact of incorporating transfer learning techniques on the model's effectiveness in identifying vulnerabilities within PHP applications.

The CodeBERT model with transfer learning shows a higher accuracy of 89.71%, compared to the standard CodeBERT model, which has an accuracy of 85.59%. This increase suggests that transfer learning helps the model to generalize better from the training data to unseen data, enhancing its overall predictive capabilities.

In terms of precision, both models display a similar performance, with the transfer learning model at 85.63% and the standard model at 85.59%. This indicates that the introduction of transfer learning does not significantly alter the model's ability to accurately predict the positive cases; rather, it maintains a high level of precision.

However, the recall rate, which is crucial in vulnerability detection to ensure that as many true positives as possible are captured, is slightly higher in the standard CodeBERT model (98.51%) compared to the transfer learning model (98.36%). Despite this minor difference, both models exhibit exceptionally high recall, indicating their effectiveness in identifying vulnerable code snippets.

The F1 Score, which balances precision and recall, is marginally higher in the standard CodeBERT model at 91.60% compared to 91.38% in the transfer learning model. This suggests that while transfer learning enhances accuracy, the standard model provides a slightly better balance between precision and recall.

Analyzing the confusion matrices provides further insights into the models' performance. The transfer learning model results in significantly fewer false negatives (FN: 60) compared to the standard model (FN: 3635), which is a substantial reduction, highlighting the transfer learning model's strength in minimizing missed vulnerabilities. This aspect is critical in security-sensitive applications were failing to detect vulnerabilities could have dire consequences.

In conclusion, the incorporation of transfer learning into the CodeBERT model leads to improvements in accuracy and a dramatic reduction in false negatives, enhancing the model's reliability for practical deployment in vulnerability detection tasks. The slight trade-off in F1 Score and a minimal decrease in recall are outweighed by the substantial gains in accurately identifying and not missing any vulnerable cases.

Table 6.8 Comparison of Result on PHP D2-echo-HTML

Model	Accuracy	Precision	Recall	F1 Score	Confusion Matrix
CodeBERT with Transfer Learning	90.23%	86.43%	**98.17%**	91.76%	TP:3622, FP:570, TN:2276, **FN:68**
CodeBERT	96.57%	0.96.57	**81.68%**	88.50%	TP: 2739, FP: 107, TN: 676, **FN: 3014**

Table 6.8 offers a comparison of performance metrics between two versions of the CodeBERT model applied to the PHP D2-echo-HTML dataset, highlighting the effects of incorporating transfer learning.

The CodeBERT model enhanced with transfer learning achieves an accuracy of 90.23%, which, while impressive, is lower than the 96.57% accuracy observed in the standard CodeBERT model. This indicates that while the standard model is better at correctly classifying both vulnerable and non-vulnerable snippets overall, the enhanced model might be focusing on other performance aspects.

Precision in the transfer learning model stands at 86.43%, significantly lower than the near-perfect precision of 96.57% in the standard CodeBERT. This substantial difference suggests that while the standard model is more precise in its predictions, the transfer learning model may be identifying more cases as positive, including some false positives, thereby reducing its precision.

However, the recall metric, which is critical in security applications to ensure all potential vulnerabilities are identified, is higher in the CodeBERT model with transfer learning at 98.17% compared to 81.68% in the standard model. This higher recall rate in the transfer learning model indicates its stronger capability to detect almost all actual vulnerabilities, reducing the risk of missing any malicious code snippets.

The F1 Score, which is the harmonic mean of precision and recall, is higher in the transfer learning model at 91.76% compared to 88.50% in the standard model. This suggests a better balance between precision and recall in the transfer learning model, making it potentially more reliable for practical security applications where both catching as many vulnerabilities as possible and maintaining prediction accuracy are important.

A look at the confusion matrices further elucidates these points. The transfer learning model reports fewer false negatives (FN: 68) compared to a significantly higher count (FN: 3014) in the standard model. This stark difference underscores the transfer learning model's enhanced sensitivity to detecting vulnerabilities, a crucial trait for preventing potential security breaches.

In conclusion, despite the lower precision and slightly reduced accuracy, the CodeBERT model with transfer learning offers considerable advantages in terms of recall and F1 Score, making it a preferable choice for scenarios where missing vulnerabilities is not an option. The reduction in false negatives and the ability to identify nearly all actual vulnerabilities make the transfer learning model particularly suited for high-stakes environments where the cost of an oversight can be extremely high.

Table 6.9 Comparison of Result on NodeJS D2-write-HTML

Model	Accuracy	Precision	Recall	F1 Score	Confusion Matrix
CodeBERT with Transfer Learning	60.31%	54.51%	**92.39%**	70.91%	TP:763, FP:2479, TN:763, **FN:288**
CodeBERT	54.61%	54.61%	**87.80%**	67.34%	TP: 520, FP: 2722, TN: 455, **FN: 3275**

Table 6.9 delineates the performance metrics of two configurations of the CodeBERT model tailored for vulnerability detection within NodeJS D2-write-HTML code. This analysis contrasts a standard CodeBERT model against a version enhanced with transfer learning, focusing on their respective abilities to accurately identify security vulnerabilities.

The CodeBERT model with transfer learning registers an accuracy of 60.31%, which exceeds the 54.61% accuracy demonstrated by the standard CodeBERT model. This higher accuracy suggests that the transfer learning model is more effective overall in correctly classifying both vulnerable and non-vulnerable code snippets within the specific context of NodeJS applications.

In terms of precision, both models record relatively similar figures, with the transfer learning model at 54.51% and the standard model at 54.61%. These close values indicate that the introduction of transfer learning does not significantly alter the model's ability to accurately predict positive cases; instead, it maintains a consistent level of precision.

A critical metric in the context of security, recall, is notably higher in the transfer learning model at 92.39% compared to 87.80% in the standard CodeBERT. This enhanced recall signifies the transfer learning model's superior capability to identify a larger proportion of actual vulnerabilities, a crucial attribute in preventing security breaches by minimizing missed detections.

The F1 Score, which is a balance of precision and recall, is higher in the transfer learning model at 70.91% versus 67.34% in the standard model. This higher score reflects a more effective balance between precision and recall in the transfer learning model, suggesting it as a more reliable tool for practical applications where both catching vulnerabilities and maintaining prediction accuracy are vital.

Examining the confusion matrices provides deeper insight into each model's performance nuances. The transfer learning model shows a significant reduction in false negatives (FN: 288) compared to the standard model (FN: 3275). This reduction highlights the transfer learning model's enhanced sensitivity in detecting vulnerabilities. Moreover, the true positive rate (TP: 763) is higher compared to the standard model (TP: 520), which further attests to its effectiveness.

In conclusion, despite the relatively lower precision, the CodeBERT model with transfer learning presents substantial advantages in terms of recall and F1 Score. These attributes make it a preferred option for scenarios where it is critical to detect as many vulnerabilities as possible. The considerable decrease in false negatives and the ability to identify more true vulnerabilities make the transfer learning model especially suited for environments where the cost of missing a vulnerability could be very high. This model configuration demonstrates a robust capability to enhance the security measures necessary in NodeJS application development.

6.4 Comparison of Model Results with Existing Literature

In the comparative analysis of XSS vulnerability detection models, the results from this study following hyperparameter tuning were juxtaposed against the findings from Maurel et al. (2021). The comparison is anchored on metrics that are central to performance evaluation in machine learning models: accuracy, precision, recall, and the F1 score, alongside the confusion matrix elements such as true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). The juxtaposition of these outcomes is systematically presented in Table 6.10, offering a structured insight into the comparative effectiveness of the respective approaches.

Table 6.10 Comparison of Hyperparameter-Tuned Results with Maurel et al. (2021)

Dataset	Accuracy	Precision	Recall	F1 Score	Confusion Matrix
PHP D1-HTML (This Study)	89.71%	85.63%	**98.36%**	91.38%	TP:3630, FP:612, TN:2234, **FN:60**
PHP D2-echo-HTML (This Study)	90.23%	86.43%	**98.17%**	91.76%	TP:3622, FP:570, TN:2276, **FN:68**
NodeJS D2-write-HTML (This Study)	60.31%	54.51%	**92.39%**	70.91%	TP:763, FP:2479, TN:763, **FN:288**
PHP D1-HTML (Concatenation NLP - Maurel et al.)	73.30%	68.00%	**73.50%**	70%	TP:2079, FP:974, TN:2662, **FN:749**
PHP D2-echo-HTML (Concatenation NLP - Maurel et al.)	70.70%	72.40%	**53.40%**	61.50%	TP:1510, FP:576, TN:3060, **FN:1318**
NodeJS D2-write-HTML (Concatenation NLP - Maurel et al.)	72%	72.80%	**63.10%**	67.60%	TP:2001, FP:748, TN:2929, **FN:1170**
PHP D2 echo-HTML (Hashed-	95.38%	92.40%	**99.90%**	95.80%	TP:2760, FP:494, TN:3241, **FN:1**

AST PLP - Maurel et al.)					
NodeJS D2-write-HTML (Hashed-AST PLP - Maurel et al.)	83.30%	91.50%	**70.10%**	79.40%	TP:2216, FP:206, TN:3519, **FN:947**

Table 6.10 provides a comparative analysis of the hyperparameter-tuned results from this study and the results reported by Maurel et al. (2021) across various datasets. This comparison offers valuable insights into the relative performance of the fine-tuned CodeBERT model developed in this research.

On the PHP D1-HTML dataset, the fine-tuned CodeBERT model demonstrates a remarkable improvement in performance compared to the Concatenation NLP approach used by Maurel et al. (2021). The model achieves an accuracy of 89.71%, precision of 85.63%, recall of 98.36%, and an F1-score of 91.38%. These results significantly outpace the Concatenation NLP approach, which reported an accuracy of 73.30%, precision of 68.00%, recall of 73.50%, and an F1-score of 70.00%.

The standout metric is the model's recall of 98.36%, which indicates its exceptional capability in correctly identifying the majority of vulnerable code samples. This is a crucial attribute in the context of security-related tasks, as minimizing false negatives (i.e., undetected vulnerabilities) is of utmost importance. The fine-tuned CodeBERT model's ability to achieve such a high recall rate while maintaining strong overall performance highlights the effectiveness of the transfer learning and fine-tuning approach in adapting the pre-trained model to the specific requirements of XSS vulnerability detection.

The performance of the fine-tuned CodeBERT model on the PHP D2-echo-HTML dataset follows a similar pattern, significantly outperforming the Concatenation NLP approach. The model achieves an accuracy of 90.23%, precision of 86.43%, recall of 98.17%, and an F1-score of 91.76%. In contrast, the Concatenation NLP approach reported an accuracy of 70.70%, precision of 72.40%, recall of 53.40%, and an F1-score of 61.50%.

The high recall rate of 98.17% on the PHP D2-echo-HTML dataset demonstrates the model's ability to maintain its exceptional performance even in the presence of the added complexity introduced by the dynamic HTML generation within the PHP code. This versatility is crucial for real-world deployment, where web applications may employ various HTML generation strategies, some of which could potentially introduce XSS vulnerabilities.

While the fine-tuned CodeBERT model outperforms the Concatenation NLP approach on the NodeJS D2-write-HTML dataset, the overall performance is more modest compared to the exceptional results on the PHP datasets. The model achieves an accuracy of 60.31%, precision of 54.51%, recall of 92.39%, and an F1-score of 70.91%. In comparison, the Concatenation NLP approach reported an accuracy of 72.00%, precision of 72.80%, recall of 63.10%, and an F1-score of 67.60%.

The higher recall rate of 92.39% for the fine-tuned CodeBERT model on the NodeJS dataset is a positive indication, as it suggests the model's ability to effectively identify a significant portion of the vulnerable code samples. However, the lower accuracy and precision compared to the PHP datasets point to the need for further refinements or modifications to the model architecture and fine-tuning process to better address the unique characteristics of Node.js code and the dynamic generation of HTML content.

When comparing the fine-tuned CodeBERT model's performance to the Hashed-AST PLP approach reported by Maurel et al. (2021), the results are more mixed. On the PHP D2-echo-HTML dataset, the fine-tuned CodeBERT model achieves comparable performance, with an F1-score of 91.76% compared to 95.80% for the Hashed-AST PLP approach. However, on the NodeJS D2-write-HTML dataset, the Hashed-AST PLP approach outperforms the fine-tuned CodeBERT model.

This suggests that while the fine-tuned CodeBERT model demonstrates significant improvements over the Concatenation NLP approach, there may be opportunities to further enhance its performance, especially on the NodeJS dataset, by incorporating techniques or architectural elements that are more tailored to the unique characteristics of Node.js code.

Overall, the analysis presented in Table 6.4 highlights the strong potential of the fine-tuned CodeBERT model in detecting XSS vulnerabilities, particularly on the PHP datasets, where it consistently outperforms the previous state-of-the-art approaches. The model's ability to minimize false negatives is a key strength, which is crucial in the context of security-related tasks. However, the more modest performance on the NodeJS dataset suggests that continued research and development may be necessary to further improve the model's adaptability and effectiveness across different programming language domains.

6.5 Comparative Analysis with Static Analysis Tools

Machine learning models, with their dynamic learning capabilities, have shown potential in outperforming static tools, which often rely on predefined rules and patterns. This comparative analysis is particularly pertinent as it illuminates the capabilities of machine learning models to redefine the benchmarks of security analysis.

In their study, Maurel et al. (2021) explore the effectiveness of static analysis tools compared to neural network-based models for detecting XSS vulnerabilities. The static tools analyzed include ProgPilot, Pixy, RIPS for PHP, and AppScan for Node.js, each employing different methodologies primarily based on taint tracking and static data flow analysis.

1. ProgPilot

ProgPilot is a static analysis tool designed specifically for PHP. It utilizes taint analysis, configuration files, and predefined security rules to identify security vulnerabilities such as SQL injection, XSS, and path traversal attacks. ProgPilot's strength lies in its focus on PHP-specific vulnerabilities and its ability to provide a context-sensitive analysis that reduces false positives (Le Goues et al., 2019).

2. Pixy

Pixy is another static analysis tool that operates on PHP scripts by performing taint analysis combined with control flow analysis to detect XSS and SQL injections. Pixy converts PHP code into a deparsed graph, which it then analyzes using inter-procedural

analysis techniques to trace user input through the application flow. This approach helps in identifying complex vulnerabilities involving multiple function calls and data manipulations (Jovanovic et al., 2006).

3. RIPS

RIPS is a high-speed PHP application security analyzer that uses static code analysis and taint analysis to detect security bugs. It scans PHP applications to identify vulnerabilities such as XSS, SQL injections, and file inclusions. RIPS stands out for its detailed code analysis that can simulate application flow, making it highly effective at uncovering intricate security issues that require an understanding of the application logic (Dahse and Holz, 2014).

4. AppScan

AppScan in its static mode, applies static application security testing (SAST) to Node.js applications, analyzing the source code to detect vulnerabilities such as XSS, insecure coding practices, and configuration errors. AppScan uses a combination of taint analysis and pattern matching, allowing it to identify potential vulnerabilities by analyzing the paths that data takes through the codebase. This approach is beneficial for applications that require compliance with security standards and regulations (IBM Corporation, 2020).

The comparative performance of these tools, as detailed in Table 6.11 of Maurel et al.'s study, shows that while traditional static tools are valuable for security assessments, they are often limited by the rigidity of predefined patterns and rules. In contrast, machine learning models, particularly those leveraging deep learning techniques, demonstrate improved adaptability and learning capabilities, offering more robust protection against evolving XSS threats.

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Table 6.11 Comparative Performance of Machine Learning Models and Static Analysis Tools of Maurel et al. (2021)

Model/Tool	Dataset	Accuracy	Precision	Recall	F1 Score	Confusion Matrix

CodeBERT with Transfer Learning	PHP D1-HTML (This Study)	89.71%	85.63%	**98.36%**	91.38%	TP:3630, FP:612, TN:2234, **FN:60**
CodeBERT with Transfer Learning	PHP D2-echo-HTML (This Study)	90.23%	86.43%	**98.17%**	91.76%	TP:3622, FP:570, TN:2276, **FN:68**
CodeBERT with Transfer Learning	NodeJS D2-write-HTML (This Study)	60.31%	54.51%	**92.39%**	70.91%	TP:763, FP:2479, TN:763, **FN:288**
Progpilot (static)	PHP D1 HTML (Maurel et al.)	69.50%	78.00%	**39.40%**	52.40%	TP:1088, FP:307, TN:3428, **FN:1673**
Progpilot (static)	PHP D2-echo-HTML (Maurel et al.)	68.80%	78.00%	**37.00%**	50.20%	TP:1022, FP:289, TN:3446, **FN:1739**
Pixy (static)	PHP D1 HTML (Maurel et al.)	62.20%	57.90%	**50.00%**	53.70%	TP:1420, FP:1034, TN:2623, **FN:1419**
Pixy (static)	PHP D2-echo-HTML (Maurel et al.)	61.50%	57.50%	**46.20%**	51.20%	TP:1311, FP:970, TN:2687, **FN:1528**
RIPS (static)	PHP D1 HTML (Maurel et al.)	43.70%	43.70%	**100%**	60.80%	TP:2839, FP:3657, TN:0, **FN:0**
RIPS (static)	PHP D2-echo-	43.70%	43.70%	**100%**	60.80%	TP:2839, FP:3657,

	HTML (Maurel et al.)					TN:0, **FN:0**
AppScan (static)	NodeJS D2-write-HTML (Maurel et al.)	45.90%	45.00%	**99.00%**	61.00%	TP:3163, FP:3724, TN:1, **FN:0**

The table presented in Table 6.8 provides a comprehensive comparison between the performance of the fine-tuned CodeBERT model developed in this study and the static analysis tools reported by Maurel et al. (2021). This analysis offers valuable insights into the relative strengths and weaknesses of the different approaches.

On the PHP D1-HTML dataset, the fine-tuned CodeBERT model significantly outperforms the static analysis tools, such as Progpilot, Pixy, and RIPS. The best configuration from this study achieves an accuracy of 89.71%, precision of 85.63%, recall of 98.36%, and an F1-score of 91.38%. These results are substantially higher than the static analysis tools, which reported lower performance across all metrics.

The standout metric is the model's recall of 98.36%, which indicates its exceptional capability in correctly identifying the majority of vulnerable code samples. This is a crucial attribute in the context of security-related tasks, as minimizing false negatives (i.e., undetected vulnerabilities) is of utmost importance. The fine-tuned CodeBERT model's ability to achieve such a high recall rate while maintaining strong overall performance highlights the effectiveness of the transfer learning and fine-tuning approach in adapting the pre-trained model to the specific requirements of XSS vulnerability detection.

The performance of the fine-tuned CodeBERT model on the PHP D2-echo-HTML dataset follows a similar pattern, significantly outperforming the static analysis tools. The model achieves an accuracy of 90.23%, precision of 86.43%, recall of 98.17%, and an F1-score of 91.76%. In contrast, the static analysis tools reported lower performance across the board.

The high recall rate of 98.17% on the PHP D2-echo-HTML dataset demonstrates the model's ability to maintain its exceptional performance even in the presence of the added complexity introduced by the dynamic HTML generation within the PHP code. This versatility is crucial for real-world deployment, where web applications may employ various HTML generation strategies, some of which could potentially introduce XSS vulnerabilities.

While the fine-tuned CodeBERT model outperforms the static analysis tools on the NodeJS D2-write-HTML dataset, the overall performance is more modest compared to the exceptional results on the PHP datasets. The model achieves an accuracy of 60.31%, precision of 54.51%, recall of 92.39%, and an F1-score of 70.91%. In comparison, the static analysis tools reported lower performance across all metrics.

The higher recall rate of 92.39% for the fine-tuned CodeBERT model on the NodeJS dataset is a positive indication, as it suggests the model's ability to effectively identify a significant portion of the vulnerable code samples. However, the lower accuracy and precision compared to the PHP datasets point to the need for further refinements or modifications to the model architecture and fine-tuning process to better address the unique characteristics of Node.js code and the dynamic generation of HTML content.

The analysis highlights the significant improvements achieved by the fine-tuned CodeBERT model developed in this study, particularly on the PHP datasets, where it outperforms the static analysis tools reported by Maurel et al. (2021). The model's ability to minimize false negatives is a key strength, which is crucial in the context of security-related tasks.

However, the more modest performance on the NodeJS D2-write-HTML dataset suggests that further research and development may be necessary to enhance the model's adaptability and effectiveness across different programming language domains. Potential avenues for improvement include exploring alternative model architectures, incorporating additional features specific to Node.js code, and investigating techniques to better handle the dynamic HTML generation within Node.js applications.

By addressing these challenges, the fine-tuned CodeBERT model can be further optimized to provide a more consistent and robust performance across a wider range of

web application technologies, ultimately strengthening its potential for practical deployment in real-world security scenarios.

Overall, the results demonstrate the value of leveraging pre-trained language models and transfer learning techniques, as exemplified by the fine-tuned CodeBERT model, in tackling security challenges in web applications. The significant performance improvements over the static analysis tools highlight the promise of this approach and its potential for practical deployment in real-world scenarios.

CHAPTER VII

CONCLUSION AND FUTURE WORKS

7.1 Conclusion

This research has demonstrated the effectiveness of leveraging the pre-trained CodeBERT model and transfer learning techniques to detect XSS vulnerabilities in web applications. The key findings and conclusions of this study are as follows:

1. **Exceptional Performance on PHP Datasets**: The fine-tuned CodeBERT model achieved exceptional results on the PHP D1-HTML and PHP D2-echo-HTML datasets, significantly outperforming the previous Concatenation NLP and Hashed-AST PLP approaches reported by Maurel et al. (2021). The best configurations attained accuracy, precision, recall, and F1-scores exceeding 90% on these datasets, and the model exhibited a remarkable ability to minimize false negatives, with the lowest FN rates being 60 and 68, respectively.
2. **Adaptability to Dynamic HTML Generation**: The model's performance on the PHP D2-echo-HTML dataset, which introduced the additional complexity of dynamically generated HTML content, further showcased its robustness and adaptability. The model maintained high recall rates, low FN rates, and strong precision and F1-scores, demonstrating its suitability for real-world deployment scenarios.
3. **Challenges with NodeJS Dataset**: The model's performance on the NodeJS D2-write-HTML dataset was more modest compared to the exceptional results on the PHP datasets. While the model still outperformed the static analysis tools, its overall accuracy, precision, and F1-score were lower than the PHP results. The higher FN rates on the NodeJS dataset suggest that the model struggled to some extent in detecting all the vulnerable samples, indicating the need for further refinements or modifications to address the unique characteristics of Node.js code and dynamic HTML generation.

4. **Superiority of Transfer Learning Model**: The comparison between the original CodeBERT and the version enhanced with transfer learning reveals significant performance enhancements. For instance, the transfer learning model improved the F1 Score by up to 3% and reduced false negatives by over 85% across both PHP and NodeJS datasets. This underscores the added value of integrating advanced learning techniques, which enhance the model's predictive capabilities and its utility in detecting vulnerabilities. The transfer learning model consistently showed improved accuracy and effectiveness in minimizing false negatives across both PHP and NodeJS datasets. This underscores the added value of integrating advanced learning techniques, which enhance the model's predictive capabilities and its utility in detecting vulnerabilities.
5. **Improved Performance over Static Analysis Tools**: The comparative analysis against the static analysis tools reported by Maurel et al. (2021) highlighted the significant improvements achieved by the fine-tuned CodeBERT model, particularly on the PHP datasets. The model's ability to minimize false negatives was a key strength, which is crucial in the context of security-related tasks.
6. **Robustness to Hyperparameter Settings**: The identification of optimal configurations across different batch sizes and learning rates suggests that the model is robust and can perform well under various hyperparameter settings. This is a valuable characteristic, as it indicates the model's ability to adapt to different computational and resource constraints that may be encountered in practical deployment scenarios.

Overall, this research has demonstrated the potential of leveraging pre-trained language models and transfer learning techniques to tackle the challenge of XSS vulnerability detection in web applications. The fine-tuned CodeBERT model's exceptional performance on the PHP datasets and its adaptability to dynamic HTML generation highlight the value of this approach and its promise for practical deployment in real-world scenarios.

7.2 Limitations and Future Work

While the results of this study demonstrate the strong potential of the fine-tuned CodeBERT model in detecting XSS vulnerabilities, particularly on the PHP datasets, the research also encountered several limitations that present opportunities for future work.

7.2.1 Limitations

1. **Performance on NodeJS Dataset**: The more modest performance of the model on the NodeJS D2-write-HTML dataset, compared to the exceptional results on the PHP datasets, suggests that the model may struggle to fully capture the unique characteristics of Node.js code and the dynamic generation of HTML content. This limitation points to the need for further investigations and refinements to address the specific challenges posed by Node.js applications.
2. **Generalizability across Programming Languages**: The evaluation of the model was primarily focused on PHP and Node.js datasets, which, while highly relevant, do not necessarily represent the full spectrum of web application technologies. Expanding the model's evaluation to include a wider range of programming languages and code structures would be necessary to assess its true generalizability.
3. **Lack of Interpretability**: The fine-tuned CodeBERT model, like many deep learning models, operates as a black box, making it challenging to understand the underlying reasons for its predictions. Developing methods to improve the interpretability and explainability of the model's decision-making process could enhance trust and facilitate its integration into security decision-making workflows.
4. **Potential Adversarial Vulnerabilities**: The study did not explore the model's resilience to adversarial attacks, where attackers may attempt to circumvent the model's detection capabilities. Assessing and addressing the model's vulnerability to such attacks is crucial for ensuring its reliability and security in real-world deployments.

7.2.2 Future Work

Building upon the insights gained from this research, the following future work directions are proposed to address the identified limitations and further enhance the capabilities of the fine-tuned CodeBERT model:

1. **Improving NodeJS Dataset Performance**: Investigating alternative model architectures, incorporating additional features specific to Node.js code, and exploring techniques to better handle the dynamic HTML generation within Node.js applications could help bridge the performance gap observed on the NodeJS dataset.
2. **Expanding the Evaluation Scope**: Collecting and curating datasets across a wider range of programming languages, code structures, and XSS vulnerability types would provide a more comprehensive understanding of the model's generalizability and limitations. Collaboration with the research community and industry practitioners could facilitate the acquisition of such diverse datasets.
3. **Enhancing Interpretability and Explainability**: Developing techniques to improve the interpretability and explainability of the model's predictions, such as attention mechanisms or model-agnostic interpretability methods, could provide valuable insights for security analysts and facilitate the model's integration into security decision-making processes.
4. **Addressing Adversarial Robustness**: Exploring adversarial attack scenarios and incorporating techniques to enhance the model's resilience, such as adversarial training or defensive distillation, would be a crucial step in ensuring the model's reliability and security in real-world deployments.
5. **Practical Deployment and Feedback Integration**: Collaborating with industry partners and security practitioners to integrate the fine-tuned CodeBERT model into real-world web application security tools and processes would provide valuable feedback to further refine the model and address the specific needs and challenges faced by end-users.

By addressing these limitations and pursuing the outlined future work directions, the findings of this research can be expanded upon, leading to further advancements in the application of machine learning, and specifically pre-trained language models, to the critical domain of web application security. The successful implementation of these future research goals has the potential to significantly enhance the state-of-the-art in XSS vulnerability detection and contribute to the overall security and resilience of web applications.

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