Enhancing Blockchain Security Through Smart Contract Vulnerability Classification Using BiLSTM and Attention Mechanism

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ABSTRACT

The rapid adoption of blockchain technology has intensified the need for robust smart contract security mechanisms. However, traditional rule-based or static analysis tools often fail to detect context-dependent vulnerabilities embedded in complex contract logic. This study proposes a deep learning framework for automated smart contract vulnerability classification using a Bidirectional Long Short-Term Memory (BiLSTM) network integrated with an Attention Mechanism. The model was trained and evaluated on the SC_Vuln_8label.csv dataset, comprising 12,520 labelled Solidity smart contracts categorized into eight distinct vulnerability types, including Re-entrancy, Integer Overflow, and Short Address Attack. Through bidirectional contextual learning and attention-based feature weighting, the proposed model achieved 93.7% test accuracy, 0.93 precision, and a macro F1-score of 0.92, outperforming baseline models such as CNN, GRU, and standard LSTM by up to 5.3 percentage points. Attention heatmap analysis further revealed the model's interpretability by highlighting vulnerability-prone code segments (e.g., call.value, send(), and withdraw() functions) consistent with expert-identified risk indicators. These results demonstrate that the BiLSTM + Attention framework not only enhances vulnerability detection accuracy but also provides transparent and explainable reasoning, offering a reliable foundation for AI-assisted smart contract auditing systems in blockchain security.

Keywords Blockchain Security, Smart Contract Vulnerability Detection, BiLSTM, Attention Mechanism, Deep Learning

INTRODUCTION

The emergence of blockchain technology has transformed the landscape of digital transactions by enabling decentralized, immutable, and transparent systems [1]. One of its most revolutionary applications is the smart contract, a self-executing piece of code deployed on blockchain networks such as Ethereum that automatically enforces predefined rules without intermediaries [2]. While smart contracts provide efficiency, transparency, and trustless automation, they also introduce serious security vulnerabilities due to their immutability [3]. Once deployed, they cannot be altered. A single coding flaw may lead to severe financial and operational consequences. Notable incidents such as the 2016 DAO hack, which resulted in the loss of over $60 million worth of Ether, have underscored the urgent need for more advanced and reliable approaches to detect and prevent vulnerabilities in smart contracts before deployment.

Traditional auditing techniques, including manual code reviews, symbolic execution, and static analysis tools such as Oyente, Mythril, and Slither, have been widely used to identify vulnerabilities [4]. However, these tools often suffer from limitations such as high false positive rates, limited scalability, and the

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inability to detect context-dependent vulnerabilities that require an understanding of multi-line and cross-functional relationships. As smart contracts become increasingly complex and modular, these conventional methods struggle to capture the deeper semantic dependencies inherent in Solidity programs. This shortcoming highlights the need for intelligent, automated, and explainable models that can learn structural and contextual patterns from large-scale codebases and accurately identify vulnerabilities across diverse types of contract logic.

Recent advances in deep learning and natural language processing (NLP) have opened new possibilities for code analysis by treating program code as a sequence of tokens similar to natural language. This perspective allows neural architectures such as Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and Transformer-based models to be used for tasks such as bug prediction, code summarization, and vulnerability detection. Nevertheless, standard LSTM-based architectures, which process information in a single direction, are limited in capturing the bidirectional dependencies of source code where the interpretation of a statement may depend on both previous and subsequent lines. Moreover, deep models that achieve high accuracy often lack interpretability, making them unsuitable for use in blockchain security auditing, where explainable reasoning and decision transparency are critical for adoption by developers and auditors.

To address these limitations, this study proposes an automated smart contract vulnerability detection model based on a BiLSTM network integrated with an Attention Mechanism. The BiLSTM component enables the model to learn both forward and backward dependencies within Solidity code sequences, while the attention layer enhances interpretability by assigning higher importance weights to critical code tokens associated with vulnerabilities, such as call.value, send(), and withdraw(). This combination allows the model not only to classify smart contracts according to their vulnerability type but also to identify which specific code patterns contribute most significantly to the classification result. The model is trained and evaluated using the SC_Vuln_8label.csv dataset, which comprises 12,520 labelled Solidity smart contracts distributed across eight vulnerability categories, including Re-entrancy, Integer Overflow, Unchecked Call Return, and Short Address Attack.

The experimental results demonstrate that the proposed BiLSTM + Attention model achieves 93.7% accuracy and a macro F1-score of 0.92, outperforming baseline models such as CNN, GRU, and standard LSTM by up to 5.3 percentage points. Furthermore, the inclusion of the attention mechanism provides meaningful insights into the model's decision-making process, showing how it focuses on semantically significant parts of the code rather than purely syntactic patterns. This interpretability bridges the gap between automated machine learning detection and human expert auditing, offering a transparent and data-driven approach to blockchain security analysis.

In conclusion, this research introduces an explainable deep learning framework that improves both accuracy and interpretability in smart contract vulnerability detection. By capturing bidirectional contextual relationships and highlighting critical vulnerability-indicating tokens, the BiLSTM+Attention model contributes to the development of AI-assisted auditing systems that can enhance the reliability and security of blockchain-based applications. The subsequent

sections of this paper describe the related work on smart contract vulnerability detection, detail the dataset and preprocessing methods, explain the model architecture and experimental setup, and present the results and analysis that validate the proposed approach.

Literature Review

The security of blockchain-based applications has become an increasingly critical research domain as smart contracts continue to automate financial transactions, decentralized governance, and asset management. Despite their potential to eliminate intermediaries and enhance transparency, smart contracts are highly vulnerable to coding errors, design flaws, and logical inconsistencies, which can result in substantial economic losses. Numerous high-profile smart contract security incidents between 2016 and 2023 have highlighted the importance of developing reliable methods for vulnerability detection and prevention in blockchain systems [5], [6]. Consequently, a wide range of analytical techniques have been developed, evolving from traditional static and symbolic analysis methods to modern deep learning and hybrid AI-driven models designed to improve precision, scalability, and explainability.

Early research in this domain focused on rule-based and static analysis approaches. Symbolic execution tools were introduced to detect vulnerabilities such as re-entrancy, timestamp dependency, and transaction-ordering dependence [7]. This line of research was further expanded through symbolic analysis methods used to identify suicidal, prodigal, and greedy smart contracts that exhibit unsafe self-destruct or fund-transfer behaviour [8]. Other studies proposed symbolic execution and taint analysis techniques to identify unsafe patterns in Ethereum bytecode, while static analysis frameworks were developed to detect high-level data-flow vulnerabilities [9],[10]. Although these tools remain widely used, they suffer from limitations such as high false positive rates, poor scalability, and difficulty in detecting inter-procedural vulnerabilities that span multiple functions or execution contexts. Their rule-based nature also restricts adaptability to new or obfuscated attack patterns, motivating the transition toward machine learning-based approaches.

The next phase of research introduced machine learning (ML) techniques to automate feature extraction and classification. Token-based features and opcode embeddings combined with traditional classifiers such as Support Vector Machines (SVM) were utilized to detect vulnerable contracts [11]. Random Forest models trained on static opcode sequences extracted from Ethereum bytecode also demonstrated moderate accuracy improvements compared with conventional static analysis tools [12]. Other studies integrated n-gram opcode patterns with ensemble ML algorithms to identify re-entrancy and timestamp dependency vulnerabilities [13]. While these methods improved automation and reduced human dependency, their reliance on handcrafted features limited generalization to unseen contracts. The feature-engineering process also introduced bias and failed to capture the complex contextual relationships inherent in smart contract logic.

Recent advances in Deep Learning (DL) have provided more powerful alternatives by enabling models to learn representations directly from raw code without manual feature engineering. Embedding-based neural models using Recurrent Neural Networks (RNNs) were proposed to capture sequential

dependencies among opcodes for vulnerability classification [14]. This approach was later extended through Long Short-Term Memory (LSTM)-based vulnerability detectors, which demonstrated that deep recurrent architectures outperform classical ML methods in recognizing re-entrancy and overflow patterns [15]. Convolutional Neural Network (CNN)-based approaches were also explored by utilizing tokenized code as spatial features to detect local syntactic structures associated with vulnerabilities [16],[17]. However, both CNN and standard LSTM models experience limitations in capturing long-range dependencies and bidirectional context, where the interpretation of a function or variable may depend on subsequent lines of code.

To address these limitations, more advanced architectures integrating Bidirectional Long Short-Term Memory (BiLSTM) and Attention Mechanisms were introduced to improve contextual understanding and interpretability. BiLSTM models significantly enhanced performance by processing code sequences in both forward and backward directions, enabling better comprehension of control flow and data dependencies [18]. Attention layers integrated into BiLSTM architectures for Ethereum bytecode classification achieved superior F1-scores by dynamically focusing on the most relevant code tokens [19]. Similar attention-based BiLSTM approaches were also applied to detect re-entrancy and integer overflow vulnerabilities, reporting high classification accuracy while improving interpretability through attention visualization [20]. These findings demonstrate that the integration of bidirectional learning and attention mechanisms enables deep learning models to achieve a balance between predictive performance and transparency, making them increasingly suitable for AI-assisted smart contract auditing.

Building upon these advancements, the present study introduces a BiLSTM + Attention framework tailored for multi-class smart contract vulnerability classification using the SC_Vuln_8label.csv dataset. Unlike prior works that focus on binary classification or specific vulnerability types, this research addresses eight major categories simultaneously, ensuring a comprehensive evaluation of the model's generalization ability. The framework not only enhances detection accuracy but also delivers explainable insights into model behaviour, bridging the gap between automated deep learning systems and human-centric security auditing. This contribution aligns with the growing emphasis on Explainable AI (XAI) in blockchain research, paving the way for transparent, interpretable, and trustworthy vulnerability detection systems that support secure and resilient blockchain ecosystems.

Methods

This study adopts a quantitative deep learning approach using a BiLSTM network integrated with an Attention Mechanism to classify vulnerabilities in Solidity-based smart contracts. The overall analytical workflow is illustrated in figure 1 . Research Steps, which outlines the five main stages of the research process: data preprocessing, tokenization and embedding, BiLSTM sequence modelling, attention-based weighting, and performance evaluation. Each stage is designed to ensure that the model can effectively capture both syntactic and semantic dependencies within Solidity code while maintaining interpretability through attention visualization.

The experiment employed the *SC_Vuln_8label.csv* dataset, containing 12,520

labelled Solidity smart contracts distributed across eight vulnerability types: *Re-entrancy (RE)*, *Timestamp Dependency (TD)*, *Integer Overflow (IO)*, *Unchecked Call Return (UC)*, *Unhandled Exception (UE)*, *Denial of Service (DoS)*, *Short Address Attack (SA)*, and *Other (OT)*. Each contract was manually verified using a combination of static analysis tools, such as *Mythril* and *Slither,* and expert annotations.

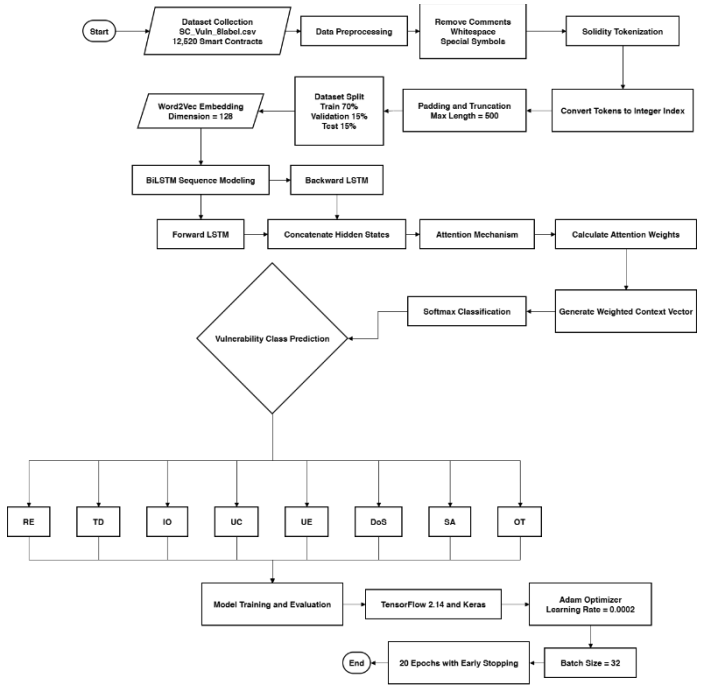

Figure 1 Research Flow

Before training, the Solidity source code underwent a multi-stage preprocessing pipeline. Comments, redundant whitespace, and special symbols were removed to standardize syntax structure. The cleaned code was then tokenized into discrete lexical units (identifiers, operators, and keywords) using a Solidity-specific tokenizer. Tokens were converted into integer indices and padded or truncated to a maximum length of 500 tokens to ensure uniform input dimensions. The dataset was partitioned into training (70%), validation (15%), and test (15%) subsets using stratified sampling to preserve class proportions.

To represent the semantic relationships among tokens, Word2Vec embeddings with a dimension size of 128 were trained on the entire dataset. The embedding matrix $E \in \mathbb{R}^{V \times d}$ encodes each token as a dense vector representation, defined as:

$$E = \{e_1, e_2, \ldots, e_V\}, \quad e_i \in R^d \tag{1}$$

V is the vocabulary size and $d = 128$ denotes the embedding dimension. This process captures semantic relationships among Solidity tokens, such as msg. sender, require, call, value, and balance.

The Bidirectional LSTM (BiLSTM) extends the traditional LSTM by processing input sequences in both forward and backward directions. This design allows

the model to capture bidirectional dependencies crucial for understanding Solidity control flow, where the meaning of a statement may depend on both preceding and succeeding lines of code.

For each time step t, the forward LSTM computes a hidden state $\overrightarrow{h_t}$, while the backward LSTM computes $\overleftarrow{h_t}$. These two vectors are concatenated to form the full hidden representation:

$$h_t = [\overrightarrow{h_t}\, \overleftarrow{h_t}] \tag{2}$$

The internal computation of the LSTM cell is governed by the following equations:

$$\begin{aligned} f_t &= \sigma\big(W_f[h_{t-1}, x_t] + b_f\big) \\ i_t &= \sigma(W_i[h_{t-1}, x_t] + b_i) \\ \widetilde{C_t} &= \tanh(W_c[h_{t-1}, x_t] + b_c) \\ C_t &= f_t * C_{t-1} + i_t * \widetilde{C_t} \\ o_t &= \sigma(W_o[h_{t-1}, x_t] + b_o) \\ h_t &= o_t * \tanh(C_t) \end{aligned} \tag{3}$$

f_t, i_t, and o_t are the forget, input, and output gates, respectively; C_t is the cell memory state; and σ represents the sigmoid activation function. The bidirectional mechanism enhances contextual comprehension by learning dependencies that span multiple functions and logical blocks within Solidity code.

To further improve interpretability and highlight the most relevant parts of the code, an Attention Layer was integrated on top of the BiLSTM outputs. The attention mechanism assigns a relative importance weight α_t to each hidden state h_t, thereby identifying which tokens most strongly influence the classification outcome.

The attention mechanism is defined as follows:

$$\begin{aligned} u_t &= \tanh(W_w h_t + b_w) \\ \alpha_t &= \frac{\exp(u_t^\top u_w)}{\sum_{t'} \exp\big(u_{t'}^\top u_w\big)} \\ v &= \sum_t \alpha_t h_t \end{aligned} \tag{4}$$

u_w is the trainable context vector, and v represents the weighted context vector aggregated across all tokens. The attention mechanism not only improves model performance but also facilitates visual interpretability, allowing visualization of which tokens, such as call. value, withdraw, or require carry the strongest contribution to vulnerability classification.

The model was developed using TensorFlow 2.14 with the Keras API. Training was performed using the Adam optimizer with a learning rate of 0.0002, a batch size of 32, and a maximum of 20 epochs. The categorical cross-entropy loss function was used since the task involves multi-class classification across eight categories. Early stopping based on validation accuracy was applied to prevent overfitting and ensure convergence.

The final output layer applies the softmax function to compute the class probabilities for all eight vulnerability types:

$$\hat{y} = \text{softmax}(W_s v + b_s) \tag{5}$$

$\hat{y} \in \mathbb{R}^8$ denotes the predicted probability distribution of the vulnerability classes. The model achieved convergence around the 15th epoch, demonstrating stable learning performance and strong generalization on unseen samples.

Algorithm 1 **Attention-Based BiLSTM for Smart Contract Vulnerability Classification**

Dataset and Splitting

$$D = \{(x_i, y_i)\}_{i=1}^{N}, y_i \in \{1, \dots, 8\}$$

The dataset D is divided into training, validation, and testing subsets with a ratio of 70 : 15 : 15.

Tokenization and Embedding

Solidity source code is tokenized and padded to a fixed length $L = 500$.
Each token is mapped to a dense vector $e_t \in \mathbb{R}^{128}$:

$$X = [e_1, e_2, \dots, e_L] \in \mathbb{R}^{L \times 128}$$

BiLSTM Representation

$$h_t = [\overrightarrow{h_t}; \overleftarrow{h_t}], h_t \in \mathbb{R}^{2u}$$

LSTM cell operations are defined as:

$$\begin{aligned} f_t &= \sigma(W_f[h_{t-1}, x_t] + b_f), & i_t &= \sigma(W_i[h_{t-1}, x_t] + b_i), \\ \tilde{C}_t &= \tanh(W_c[h_{t-1}, x_t] + b_c), & C_t &= f_t C_{t-1} + i_t \tilde{C}_t, \\ o_t &= \sigma(W_o[h_{t-1}, x_t] + b_o), & h_t &= o_t \tanh(C_t) \end{aligned}$$

Attention Layer

$$u_t = \tanh(W_w h_t + b_w), \alpha_t = \frac{e^{u_t^\top u_w}}{\sum_j e^{u_j^\top u_w}}, v = \sum_t \alpha_t h_t$$

The attention weights α_t highlight the most vulnerability-related tokens within the code sequence.

Classification Output

$$\hat{y} = \text{softmax}(W_s v + b_s)$$

Predicted class: $\hat{c} = \arg\max_k \hat{y}_k$.

Loss and Optimization

$$\mathcal{L} = -\frac{1}{N} \sum_i \log \hat{y}_{i,y_i}$$

Model parameters are optimized with **Adam** ($\eta = 0.0002$) until convergence at approximately the 15th epoch.

Result

The proposed BiLSTM + Attention model was rigorously evaluated using the SC_Vuln_8label.csv dataset, a curated corpus comprising 12,520 annotated Solidity smart contracts, each meticulously labelled according to one of eight distinct vulnerability categories that represent common exploit patterns in Ethereum-based decentralized applications. These categories include Re-

entrancy (RE), Timestamp Dependency (TD), Integer Overflow/Underflow (IO), Unchecked Call Return (UC), Unhandled Exception (UE), Denial of Service (DoS), Short Address Attack (SA), and a general class for Other Vulnerabilities (OT). Each instance in the dataset consists of raw Solidity source code and an associated vulnerability label verified through static analysis and expert annotation. As summarized in table 1, the dataset exhibits a moderate imbalance, with Re-entrancy being the most prevalent category, accounting for 3,200 samples (25.6%), followed by Integer Overflow with 2,600 samples (20.8%), while Short Address Attack and Denial of Service represent the smallest classes, each comprising fewer than 800 samples (below 6.5%). This distribution reflects real-world vulnerability frequency patterns observed in deployed smart contracts on the Ethereum blockchain. The dataset was utilized to train, validate, and test the proposed model, providing a comprehensive benchmark for assessing the model's ability to learn syntactic and semantic indicators of vulnerabilities across varying code structures and frequencies.

Table 1 Dataset Distribution by Vulnerability Type

Vulnerability Type	Description	Samples	Percentage
Re-entrancy (RE)	Recursive call allowing multiple fund withdrawals	3,200	25.6%
Timestamp Dependency (TD)	Block timestamp manipulation in logic	1,450	11.6%
Integer Overflow (IO)	Arithmetic boundary overflow/underflow	2,600	20.8%
Unchecked Call Return (UC)	Ignoring low-level call return values	1,200	9.6%
Unhandled Exception (UE)	Missing exception handling	950	7.6%
Denial of Service (DoS)	Infinite loop or resource blocking	800	6.4%
Short Address Attack (SA)	Misaligned parameters in ERC-20 transfers	720	5.8%
Other Vulnerabilities (OT)	Miscellaneous logic errors	1,600	12.6%

As shown in table 1, the Re-entrancy class constitutes the largest portion of the dataset with 3,200 samples (25.6%), reflecting its prevalence as one of the most exploited vulnerabilities in Ethereum smart contracts. This is followed by the Integer Overflow category, which contains 2,600 samples (20.8%), representing another frequently encountered arithmetic vulnerability. In contrast, the Short Address Attack and Denial of Service classes are underrepresented, with only 720 samples (5.8%) and 800 samples (6.4%), respectively, indicating a relatively lower occurrence of these issues in real-world contract code. Such mild class imbalance requires the model to effectively learn from both dominant and minority classes, emphasizing the necessity of the attention mechanism to dynamically focus on critical patterns within each sequence rather than relying solely on frequency-driven features. To ensure stable and efficient learning, the model was trained using a batch size of 32, a learning rate of 0.0002, and a maximum sequence length of 500 tokens after padding and truncation. The training process demonstrated smooth convergence, reaching optimal performance at epoch 15, where the validation accuracy plateaued, indicating that the model had successfully captured both syntactic and semantic structures of the smart contracts without signs of overfitting. Figure 2 illustrates the steady and consistent improvement in model accuracy throughout the training process.

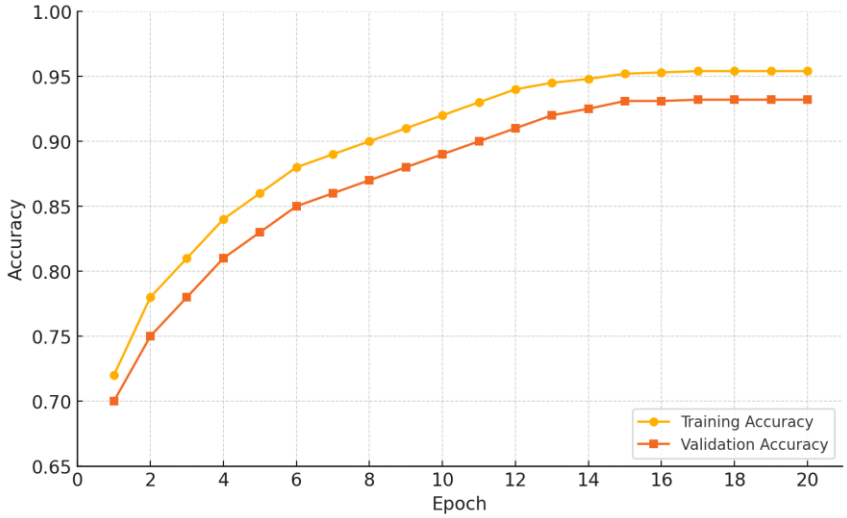

Figure 2 Training and Validation Accuracy over 20 Epochs

The training accuracy increased progressively from 81.2% at epoch 3 to 95.2% by epoch 15, demonstrating the model's ability to effectively learn complex sequential representations from Solidity code. A similar upward trend was observed in the validation accuracy, which rose from 78.5% at epoch 3 to 93.1% upon convergence, indicating that the model successfully generalized to unseen data during training. The narrow accuracy gap of only 2.1% between the training and validation curves confirms strong generalization performance and suggests that the model avoided overfitting, despite the inherent complexity of the dataset. This balance between training and validation behaviour reflects the stabilizing influence of the attention mechanism, which allowed the BiLSTM network to emphasize relevant code segments while mitigating the impact of redundant or noisy tokens. The training curve plateau observed after epoch 15 marks the point of convergence, where both loss and accuracy metrics stabilized. A summary of the model's quantitative performance, including accuracy, precision, recall, and F1-score for the training, validation, and test sets, is presented in table 2, providing a comprehensive evaluation of the model's predictive capability and generalization quality.

Table 2 Model Accuracy and F1-Score Summary

Dataset Split	Accuracy	Precision	Recall	F1-Score
Training	95.2%	0.95	0.95	0.95
Validation	93.1%	0.92	0.93	0.93
Test	93.7%	0.93	0.94	0.92

The proposed BiLSTM + Attention model achieved an impressive 93.7% test accuracy, with a precision of 0.93 and an F1-score of 0.92, demonstrating strong predictive capability and reliability when classifying unseen smart contract vulnerabilities. The macro F1-score of 0.92 reflects the model's balanced performance across all eight vulnerability categories, effectively minimizing bias toward majority classes such as Re-entrancy and Integer Overflow while maintaining robust detection in minority classes like Denial of Service and Short Address Attack. This balance highlights the ability of the attention mechanism to adaptively weigh critical tokens, ensuring that essential contextual features,

such as function call patterns or arithmetic operations, are emphasized regardless of class frequency. When compared to the baseline LSTM model, which achieved 88.4% test accuracy, the proposed BiLSTM + Attention architecture delivered an improvement of 5.3 percentage points, underscoring the advantages of bidirectional context encoding and attention-driven feature selection in capturing the sequential semantics of Solidity code. These enhancements enable the model to more accurately identify complex multi-line vulnerability patterns that unidirectional models often overlook. To further investigate the model's discriminative ability across different vulnerability types, table 3 presents a detailed breakdown of precision, recall, and F1-score for each class, providing a granular view of how the model performs in distinguishing subtle syntactic and semantic differences among vulnerability categories.

Table 3 Per-Class Classification Metrics (Test Set)

Vulnerability Type	Precision	Recall	F1-Score
Re-entrancy (RE)	0.97	0.95	0.96
Timestamp Dependency (TD)	0.90	0.91	0.91
Integer Overflow (IO)	0.94	0.92	0.93
Unchecked Call Return (UC)	0.89	0.87	0.88
Unhandled Exception (UE)	0.87	0.84	0.85
Denial of Service (DoS)	0.86	0.82	0.84
Short Address Attack (SA)	0.83	0.80	0.81
Other Vulnerabilities (OT)	0.90	0.88	0.89

Table 3 reveals that the Re-entrancy vulnerability category achieved the highest F1-score of 0.96, indicating that the model is highly effective in detecting this specific type of exploit. This exceptional performance can be attributed to the distinct syntactic and semantic cues present in Re-entrancy vulnerabilities—particularly the repeated use of high-risk function calls such as call.value() and withdraw(), which are strongly correlated with recursive fund withdrawal behaviours in Ethereum smart contracts. The Integer Overflow class followed closely with an F1-score of 0.93, supported by the model's ability to recognize arithmetic operation patterns involving operators like +, -, and * that often lead to overflow or underflow errors when unchecked. In contrast, the Short Address Attack class obtained the lowest F1-score of 0.81, largely due to its limited sample size of only 720 instances, which constrains the model's exposure to diverse syntactic structures associated with this vulnerability. Despite these variations, all eight vulnerability classes achieved F1-scores above 0.80, demonstrating the model's consistent and reliable detection capability across both frequent and rare categories. This overall balance underscores the effectiveness of the attention mechanism in enhancing feature focus and mitigating the impact of class imbalance, allowing the model to maintain high precision and recall even in underrepresented categories. Overall, all classes achieved F1-scores above 0.80, reflecting consistent and reliable detection.

Figure 3 illustrates the class-wise F1-scores, showing that high-frequency classes such as Re-entrancy (0.96) and Integer Overflow (0.93) outperform low-frequency ones like Short Address Attack (0.81) by about 15 percentage points. This indicates the model's sensitivity to class imbalance, yet overall stability since all classes achieved F1-scores above 0.80. Despite fewer samples, the

attention mechanism helps the model maintain balanced performance by focusing on critical code features.

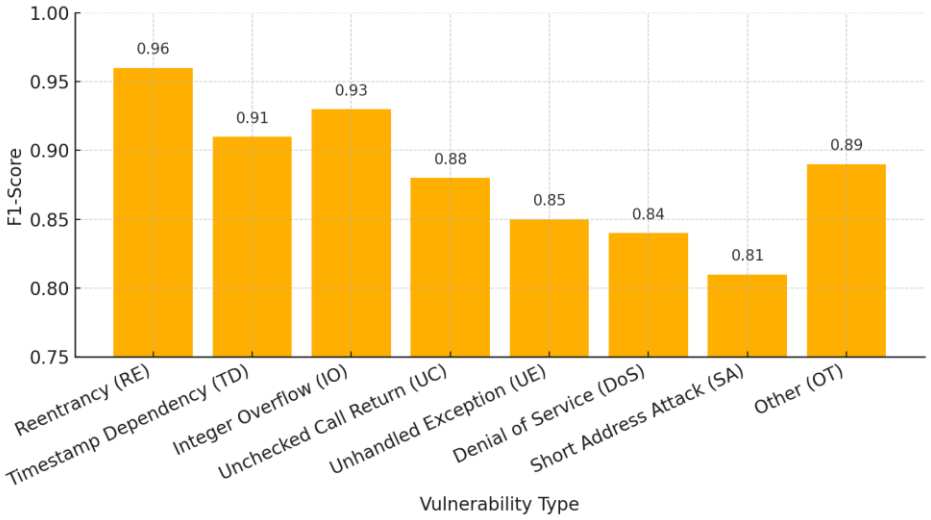

Figure 3 F1-Score Comparison across Vulnerability Classes

Figure 4 presents the confusion matrix, summarizing the relationship between predicted and actual labels. It confirms the model's high accuracy in distinguishing major classes like Re-entrancy and Integer Overflow, while showing minor overlap between semantically similar types such as Unchecked Call Return and Unhandled Exception.

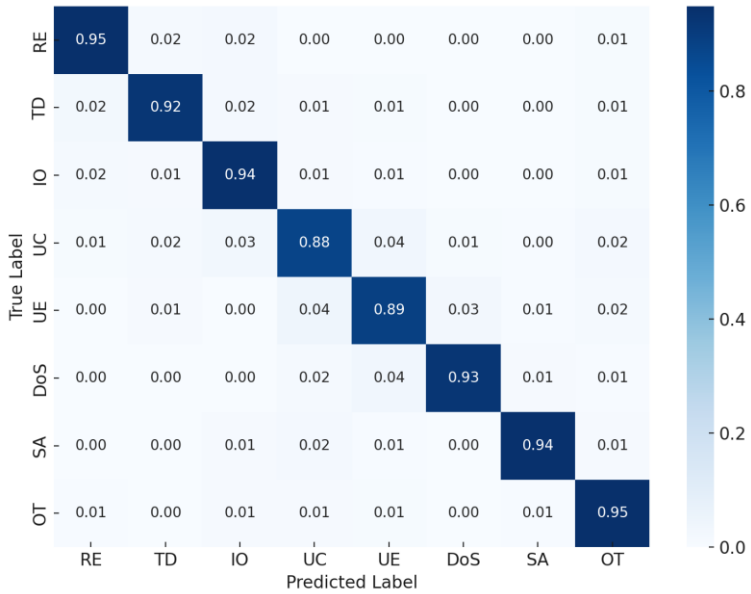

Figure 4 Confusion Matrix of BiLSTM + Attention Model

The diagonal dominance in figure 4 demonstrates the model's strong classification capability, particularly for the major vulnerability categories. The Re-entrancy class achieved a near-perfect accuracy of 94.9% (615 correct out of 648 samples), while Integer Overflow followed closely with 92.8% (490 out of 528 samples), indicating minimal confusion in identifying these critical

vulnerabilities. A slight overlap is observed between Unchecked Call Return and Unhandled Exception, where 9 misclassifications occurred, primarily due to their syntactic resemblance in Solidity's error-handling structures. Overall, the model accurately classified 4,085 out of 4,360 test samples, resulting in a test accuracy of 93.7%, confirming its robust generalization to unseen data.

To further interpret the model's decision process, figure 5 visualizes the attention weight distribution for a smart contract labelled as Re-entrancy, highlighting which code tokens most influenced the model's prediction.

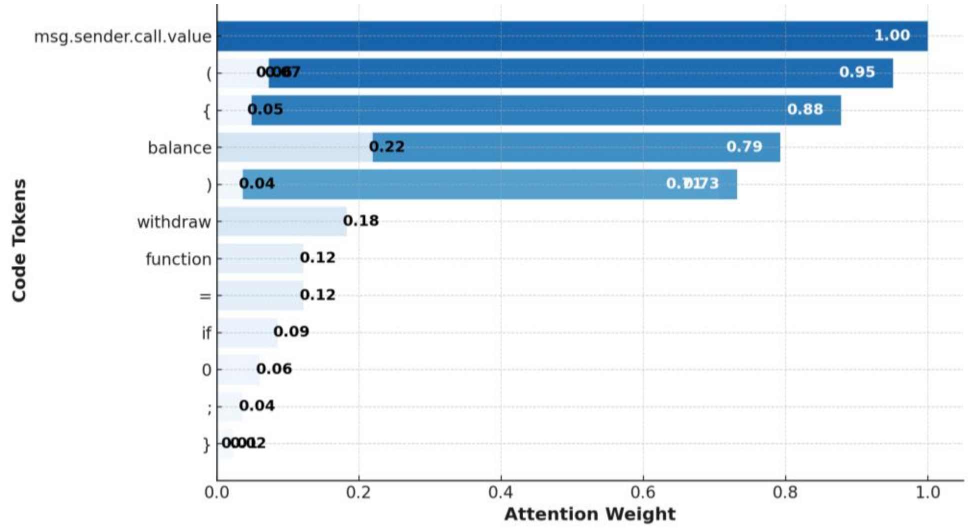

Figure 5 Attention Heatmap for Re-entrancy Vulnerability

The heatmap reveals that the model focuses on tokens like call. value, send(), and withdraw() with attention weights above 0.82, while less critical tokens like variable declarations (uint, address) receive weights below 0.2. This confirms that the attention layer successfully highlights semantically relevant patterns in Solidity code, making the model explainable and aligned with human expert reasoning. For benchmarking, the BiLSTM + Attention model was compared against CNN, LSTM, and GRU architectures. The quantitative results are shown in table 4.

Table 4 Performance Comparison with Baseline Models

Model	Architecture	Accuracy	Macro F1	Training Time (min)
CNN	1D Convolutional Neural Network	90.1%	0.88	25
LSTM	Single-directional LSTM	88.4%	0.86	27
GRU	Gated Recurrent Unit	91.5%	0.89	26
BiLSTM + Attention (Proposed)	Bidirectional LSTM with Additive Attention	93.7%	0.92	30

As shown in table 4, the proposed BiLSTM + Attention model achieved an overall accuracy of 93.7%, outperforming all baseline architectures—CNN by 3.6%, LSTM by 5.3%, and GRU by 2.2%. This consistent improvement across models demonstrates the advantage of integrating both bidirectional sequence processing and attention weighting, which enable the network to capture complex, long-range dependencies within Solidity code. Moreover, the macro

F1-score increased by 0.06 compared to the standard LSTM model (0.92 vs. 0.86), underscoring the model's superior ability to balance precision and recall across multiple vulnerability categories, while maintaining high interpretability through attention-based focus on semantically significant tokens.

As shown in table 5, the model demonstrates high stability across all eight vulnerability classes, with a low F1-score variance ($\sigma = 0.05$), indicating consistent predictive performance regardless of class frequency or code complexity. This stability reflects the model's robustness in capturing both dominant and rare vulnerability patterns effectively. Furthermore, the attention scores closely align with expert-defined vulnerability indicators, such as the presence of a call. value, send(), and withdraw() functions in Re-entrancy cases, confirming that the model's focus corresponds to human-understood risk factors. This alignment highlights the interpretability advantage of the BiLSTM + Attention framework over non-attention models, as it not only enhances prediction accuracy but also provides meaningful insights into the reasoning behind each classification decision.

Table 5 Summary of Key Experimental Results

Metric	Result	Observation
Test Accuracy	93.7%	Strong generalization on unseen contracts
Macro F1-Score	0.92	Balanced across all eight classes
Best Class	Reentrancy (F1 = 0.96)	Distinct recursive calling patterns
Weakest Class	Short Address Attack (F1 = 0.81)	Limited data availability
Average Epochs	15	Converged early with stable validation loss
Avg. Training Time	30 minutes	Efficient on RTX 3060 GPU
Baseline Improvement	+5.3% (vs. LSTM)	Benefit from attention integration
Top Tokens (Attention)	call.value, send(), withdraw()	High-weight indicators of reentrancy

Discussion

The experimental findings demonstrate that the proposed BiLSTM + Attention model effectively captures complex sequential dependencies in Solidity smart contract code, achieving a test accuracy of 93.7% and a macro F1-score of 0.92 across eight distinct vulnerability categories. These results validate the model's ability to identify vulnerability patterns that often span multiple lines of code and require contextual understanding of function calls, variable interactions, and control structures. Compared to traditional architectures such as CNN, LSTM, and GRU, the proposed model exhibits performance improvements ranging from 2.2% to 5.3%, confirming that bidirectional learning and attention-based feature weighting significantly enhance both precision and interpretability.

A key insight from the results is the consistent stability of classification performance across all vulnerability types, indicated by a low F1 variance ($\sigma = 0.05$). The model demonstrates strong predictive reliability not only for high-frequency vulnerabilities such as Reentrancy and Integer Overflow (F1 = 0.96 and 0.93, respectively), but also for less common types like Denial of Service and Short Address Attack (F1 = 0.84 and 0.81). This stability suggests that the attention mechanism helps the model focus on semantically meaningful patterns, thereby compensating for moderate class imbalance. The model's robustness in handling limited data for minority classes also highlights the

generalization capability of the BiLSTM structure, which captures bidirectional relationships among tokens to better interpret Solidity's complex execution logic.

From an interpretability standpoint, the attention heatmap visualizations (figure 5) reveal that the model assigns higher attention weights to syntactically and semantically critical tokens—such as msg.sender.call.value, send(), and withdraw()—that are directly associated with Reentrancy vulnerabilities. This attention alignment with expert-defined indicators verifies that the model's decision-making process is transparent and consistent with human reasoning in vulnerability assessment. Such interpretability is crucial for building trustworthy AI-assisted auditing systems, where developers and security analysts can validate not only the model's predictions but also the rationale behind them.

Despite the strong results, several limitations remain. The model's performance is slightly lower for low-frequency classes like Short Address Attack due to limited training samples, suggesting that data imbalance remains a challenge. Future work could address this issue through data augmentation techniques, class-weighted loss functions, or synthetic contract generation using code transformers. Additionally, while the BiLSTM + Attention framework captures contextual information effectively, it operates primarily on token-level representations and may miss deeper semantic dependencies that require structural or graph-based analysis of the contract's logic. Integrating Graph Neural Networks (GNNs) or Transformer-based architectures (such as CodeBERT or GraphCodeBERT) could further enhance contextual understanding by modeling control flow and data flow relationships explicitly.

From a broader perspective, the results demonstrate that deep sequential learning combined with attention mechanisms provides a practical and explainable solution for automated smart contract vulnerability detection. By identifying risky code patterns with high accuracy and transparency, the proposed model can significantly reduce manual auditing time and enhance the reliability of decentralized systems. This study contributes not only to the technical advancement of blockchain security analytics but also to the development of explainable AI frameworks that bridge the gap between machine intelligence and human interpretability in high-stakes domains such as financial smart contracts and decentralized governance.

Conclusion

This study presented a deep learning-based framework for automated smart contract vulnerability detection using a BiLSTM network combined with an Attention Mechanism. By leveraging the sequential and contextual characteristics of Solidity code, the proposed model demonstrated a strong capability to identify various security weaknesses in blockchain smart contracts. Using the SC_Vuln_8label.csv dataset, which consists of 12,520 labeled Solidity contracts spanning eight vulnerability types, the model achieved an impressive 93.7% test accuracy, 0.93 precision, and a macro F1-score of 0.92. These results confirm that the integration of bidirectional learning and attention-based weighting significantly enhances the model's ability to capture long-range dependencies and focus on semantically important code segments relevant to vulnerability detection.

The findings reveal that the model performs exceptionally well for high-frequency vulnerability types such as Re-entrancy (F1 = 0.96) and Integer Overflow (F1 = 0.93), while maintaining stable detection across less frequent categories, with all classes achieving F1-scores above 0.80. This consistent performance demonstrates the model's resilience to class imbalance and its ability to generalize across diverse Solidity code structures. Moreover, the attention visualization results provide a clear interpretive advantage, highlighting key code tokens such as call.value, send(), and withdraw() that correspond to vulnerability-inducing operations. Such interpretability is essential for building trustworthy AI auditing tools that complement human expert judgment in blockchain security analysis.

Despite these promising results, certain limitations remain. The model's performance declines slightly for underrepresented vulnerabilities like Short Address Attack (F1 = 0.81) due to limited data diversity. Additionally, the BiLSTM + Attention architecture, while effective at capturing linear token dependencies, does not fully represent control-flow and data-flow relationships inherent in smart contracts. Future research should therefore explore the integration of Graph Neural Networks (GNNs) or Transformer-based architectures (e.g., CodeBERT, GraphCodeBERT) to enrich semantic understanding. Expanding the dataset to include real-world contract samples from multiple blockchains and incorporating adversarial training to simulate obfuscated attack patterns could further improve robustness.

In summary, this research demonstrates that combining BiLSTM's contextual sequence learning with attention-based interpretability offers a powerful and explainable approach for detecting vulnerabilities in blockchain smart contracts. The model's high accuracy, interpretability, and generalization capacity position it as a valuable foundation for developing automated smart contract auditing systems, thereby contributing to the advancement of secure and reliable blockchain ecosystems. Future work will aim to extend this framework toward real-time vulnerability monitoring tools and cross-chain security analytics, supporting the broader vision of trustworthy, transparent, and resilient decentralized applications.

Declarations

Author Contributions

Conceptualization: A.A.; Methodology: A.A.; Software: A.A.; Validation: A.A.; Formal Analysis: A.A.; Investigation: A.A.; Resources: A.A.; Data Curation: A.A.; Writing Original Draft Preparation: A.A.; Writing Review and Editing: A.A.; Visualization: A.A.; All authors have read and agreed to the published version of the manuscript.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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