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Original Article

AI-Based Smart Contract Analysis for Digital Transactions

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ABSTRACT

Blockchain technology has transformed digital transactions into decentralized, transparent, and immutable systems. Smart contracts running on platforms like Ethereum enable automated agreements without intermediaries, but they remain vulnerable to logical errors and security risks that can lead to financial losses. This paper presents a systematic study on AI-based smart contract analysis, using machine learning and deep learning to detect vulnerabilities, anomalies, and potential risks. It proposes a hybrid model combining static analysis (code-level error detection), dynamic analysis (runtime monitoring), and supervised/unsupervised learning techniques. Feature extraction methods convert contract code into formats suitable for AI processing. The approach integrates rule-based systems with AI models to improve detection accuracy and reduce false positives. Evaluation on benchmark datasets shows better performance than traditional methods. The study highlights the effectiveness of AI in enhancing smart contract security and suggests future work on explainable AI, real-time monitoring, and cross-platform interoperability.

KEYWORDS

Smart Contracts, Artificial Intelligence, Blockchain Security, Digital Transactions, Machine Learning, Vulnerability Detection, Static Analysis, Dynamic Analysis, Ethereum, Deep Learning.

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1. INTRODUCTION

1.1. Background

The blockchain technology has revolutionized the digital economy whereby it allows secure, transparent and decentralized transactions without involving intermediaries. The key element of this innovation is smart contracts initially introduced by Nick Szabo, which are self-executing programs that enforce agreements under particular predefined circumstances once they are met. Ethereium and other platforms have been instrumental in the mainstreaming of smart contracts, which can be used in a broad variety of applications in fields like finance, healthcare, supply chain management, and governance. Nevertheless, regardless of their benefits, smart contracts are also very vulnerable to the risk of vulnerabilities due to coding errors, logical attacks, and unexpected interactions. The occurrence of high-profile cases of reentrancy attacks and integer overflow bugs has revealed the serious security implications, which cost companies money and diminished confidence in blockchain systems. Such difficulties point to the weaknesses of conventional verification and testing methods, which tend to struggle with the growing complexity, size, and dynamic nature of modern smart contracts and thus require more sophisticated and intelligent methods of analysis.

1.2. Needs of AI-Based Smart Contract Analysis

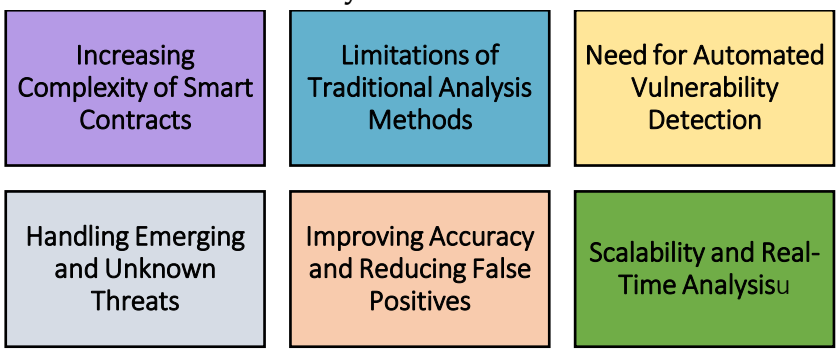

Fig 1 - Needs of AI-Based Smart Contract Analysis

1.2.1. Increasing Complexity of Smart Contracts

The contemporary smart contracts have evolved beyond the simple transaction scripts to multifaceted, decentralized applications that have numerous functions, external interactions, and layered logic. Such complexity renders manual auditing and conventional methods of analysis inadequate as they cannot represent every potential execution path and edge case. To detect vulnerabilities in large and complex codebases, AI-based solutions are required to be able to analyze them efficiently and ensure rapid and more precise detection of vulnerabilities.

1.2.2. Limitations of Traditional Analysis Methods

More traditional algorithms like formal verification and static analysis can be highly false positive or demand a lot of expertise and computation. The methods are not scalable easily and might not identify some hidden or emerging vulnerabilities. The limitations are resolved by smart

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contract analysis based on AI, which learns trends in the data and evolves with emerging threats, enhancing the accuracy of detection and minimizing the need for human intervention.

1.2.3. Need for Automated Vulnerability Detection

As the number of applications of blockchain rapidly grows, the number of deployed smart contracts has also grown considerably. This generates the high demand of automated tools capable of measuring the security of contracts in a fast and reliable way. The AI-powered system can be used to detect the process, which saves time and effort spent on auditing and provides a consistent and scalable analysis of a large quantity of contracts.

1.2.4. Handling Emerging and Unknown Threats

The vulnerabilities of Smart contracts are dynamic as the attackers keep creating exploitation methods. The conventional rule-based systems have a limited capacity to detect new threats since their vulnerabilities are only known. The AI models especially machine learning and deep learning can discern concealed patterns and abnormalities and thus they are highly effective in detecting vulnerabilities that were never known previously and in adapting to evolving security environments.

1.2.5. Improving Accuracy and Reducing False Positives

The detection accuracy versus false positive rate is one of the major challenges in smart contract analysis. False alarms are also excessive and may overload developers and erode confidence in analysis tools. The AI-driven approaches are more accurate and work with real-world data, learning to differentiate between real vulnerabilities and innocent code patterns and produce more credible and specific outputs.

1.2.6. Scalability and Real-Time Analysis

With the expansion of blockchain networks, smart contracts need to be analyzed in real time, and scalable solutions have to be developed. The systems based on AI are able to work with big datasets effectively and facilitate the constant monitoring of implemented contracts. This allows vulnerabilities to be identified beforehand and provides continuity of security that is essential to keep the trust of decentralized systems.

1.3. Smart Contract Analysis for Digital Transactions

The analysis of smart contracts is a significant issue in the safety, stability, and efficiency of digital transactions in blockchain environments. Smart contracts are used at a large scale on cryptocurrency systems like Ethereum to enforce a set of rules that allow an agreement to be automatically executed without involving middlemen. Although this automation is better in terms of transparency and low cost of operation, it also poses serious risks when the contract code has weaknesses. The mistakes, including reentrancy attacks, integer overflows, and inadequate access controls, may cause serious financial loss and deny integrity to the digital transactions. Thus, it is necessary to analyze smart contracts in detail prior to deployment and throughout their lifecycle. There are various techniques that are used in smart contract analysis and these include static analysis,

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dynamic testing and formal verification to detect possible security flaws. The code is analyzed at the point of execution to identify any vulnerable patterns in the code and at the point of contract execution to identify any problems that arise under a certain condition, in dynamic analysis. This process has been further improved in recent years, with the help of AI based techniques that allow automated and intelligent identification of vulnerabilities based on pattern recognition and anomaly detection. These sophisticated methods can be utilized to conduct analysis faster and more scalably, especially in situations where a large number of transactions and contracts occur. Secure smart contract analysis in the digital transaction context allows to ensure trust among participants by ensuring that transactions are performed correctly and without manipulation. It also assists in compliance in regulation and minimizes the chances of conflicts as a result of poor implementation of the contract. With the ongoing spread of the blockchain technology to other fields like the financial sector, supply chain, and in the healthcare sector, the value of a strong analysis of smart contracts gains even greater relevance. Finally, the inclusion of novel analytical tools, particularly AI-based remedies, is necessary to ensure the integrity, security, and reliability of the digital transaction systems.

2. LITERATURE SURVEY

2.1. Traditional Smart Contract Analysis

The conventional smart contract analysis tools are mainly based on the techniques of static analysis and symbolic executions to detect the vulnerabilities in the programs that run on blockchains. Smart contract debugging tools, including Oyente and Mythril, analyze smart contract bytecode at compile time, enabling early warning of bugs such as reentrancy, integer overflow, and unhandled exceptions. These are beneficial as it does not need any runtime information, and contracts can be analyzed prior to deployment. Nevertheless, they tend to generate high false positives because they make conservative assumptions in the analysis. Also, they find it difficult to model complex contract behaviors with accuracy and in particular when external interactions or dynamic conditions are at play which restricts their utility in real world situations.

2.2. Formal Verification Methods

Formal verification is a rigorous mathematical approach that can be used to verify that smart contracts are correct and secure. These techniques can be used to ensure that a contract will act as expected in every possible situation by formally writing the logic of a contract and applying a theorem prover or model checker. This method is commonly considered to be one of the most effective ones in removing the critical vulnerabilities. Nonetheless, it is a complex process that demands profound knowledge of formal techniques and specialized instruments, is less available to general developers. In addition, the computation cost and time taken to verify a contract is considerably high with the size and complexity of the contract, and it is difficult to scale to a large or quickly changing blockchain application.

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2.3. Machine Learning Approaches

The use of machine learning-based methods has become a strong alternative to smart contract analysis, exploiting data-driven methods. The trained supervised learning models are trained with labeled datasets of vulnerable and non-vulnerable contracts to identify new contracts according to patterns learnt during training. Conversely, unsupervised learning methods detect anomalies or abnormalities which could be signs of vulnerabilities. Neural networks and other sophisticated deep learning models are particularly useful in identifying complex patterns in smart contract code and transaction behavior. Such strategies provide better flexibility and scalability than the old ones. Nonetheless, their performance is very much dependent on the quality and magnitude of training data and might be not interpretable and it is hard to comprehend the justification of some predictions.

2.4. Hybrid Approaches

Hybrid methods combine rule-based analysis with machine learning methods to address the weakness of single methods. These systems can be more accurate and have lower false positives by using both the tools of the static analysis and intelligent models. An example is that rule-based systems can initially remove clear vulnerabilities, and machine learning models can then examine more complicated patterns and edge cases. Such a layered approach will boost its detection capabilities and overall efficiency. The emerging popularity of hybrid techniques is motivated by the fact that they strike a balance between precision, scalability, and automation, which is appropriate in a real world of smart contract auditing and deployment.

3. METHODOLOGY

3.1. Proposed Framework

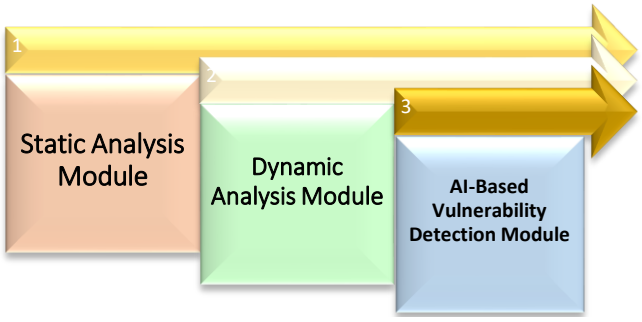

Fig 2 - Proposed Framework

3.1.1. Static Analysis Module

The Static Analysis Module will analyze the smart contract code and not run the code, allowing the origin of possible vulnerabilities to be identified before implementation. This module is used to scan the source code or the bytecode of the contract with a set of predefined rules and pattern-matching algorithms to find common vulnerabilities that include reentrancy, integer overflows, and inadequate access control. This stage is normally combined with tools such as Oyente and Mythril to conduct automated scans. The main strength of the static analysis is its efficiency and

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its capacity to analyze all the possible paths of execution, but it can produce false positives because of its conservative nature and absence of a runtime environment.

3.1.2. Dynamic Analysis Module

The Dynamic Analysis Module is used to analyze smart contracts as they run in a controlled or simulated setting, like a test blockchain or sandbox. This module can observe the contract behavior in real-time, enabling it to identify vulnerabilities that only become apparent during execution such as runtime errors, inefficiency in gas usage, and unforeseen interactions with other external contracts. Dynamic analysis is used to give more insight into contract behavior and compensates the shortcomings of the static analysis through the creation and testing of different input scenarios. This method can be computationally costly and time-consuming although more precise in some scenarios, particularly in the search of multiple execution paths.

3.1.3. AI-Based Vulnerability Detection Module

The AI-Based Vulnerability Detection Module is an open-source machine learning and deep learning-based tool that improves the precision and scalability of smart contract analysis. This module is conditioned on known vulnerable and secure contract datasets, and therefore, it can identify complex patterns and hidden relationships that would not be identified by traditional methods. Neural networks, natural language processing of code, and anomaly recognition are the techniques which are used to detect both known and new threats. The AI module can adjust to changing patterns of attacks by regularly updating itself based on new data and thus enhances its detection performance with time. This element greatly minimizes false positives and improves automation, which is why it is an important aspect of the suggested framework.

3.2. System Architecture

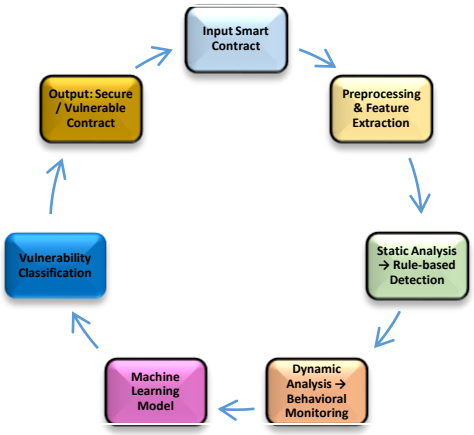

Fig 3 - System Architecture

3.2.1. Input Smart Contract

This system commences with the input of a smart contract, which can either be low-level or high-level (written in Solidity) or can be in compiled form (bytecode). This element is the gateway to

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the architecture, and it is the place where the contract is presented to the security review. The quality and completeness of the input are influential determinants of the success of later analysis processes. To achieve reliable results when analysing the contract logic, proper formatting, inclusion of all dependencies and proper visualisation of the contract logic are necessary.

3.2.2. Preprocessing & Feature Extraction

During this step, the input smart contract is preprocessed to convert it into a structured format to analyze it. This involves code normalization, elimination of redundant items, and translation into an intermediate representation like abstract syntax trees (ASTs) or control flow graphs (CFGs). Relevant attributes are then determined using feature extraction techniques including opcode sequences, function calls, and transaction patterns. Such extracted features are used to determine vulnerabilities effectively and accurately through rule-based analysis and machine learning models.

3.2.3. Static Analysis → Rule-based Detection

The phase of the static analysis uses rule-based methods to analyse the contract without executing it. Common problems which are reentrancy attacks, arithmetic errors, and improper access controls are detected using predefined security rules and vulnerability signatures. This step is fast to detect familiar vulnerabilities through a scan of code patterns and logical structures. Although efficient and offering timely feedback, the fact that it is based on predefined rules can restrict its capability to identify new or more complex vulnerabilities.

3.2.4. Dynamic Analysis → Behavioral Monitoring

The dynamic analysis component considers the smart contract when it is running in a simulated or controlled environment. It observes the behavior of runtime, such as the change of state, flow of transactions, and communication with other contracts. This module can reveal weaknesses that are only discovered at runtime, e.g. state transitions that are non-obvious, or gas-related problems. Monitoring of behavior increases the effectiveness of detection and offers useful information on the performance of the contract in various circumstances.

3.2.5. Machine Learning Model

The machine learning model then takes the extracted features and the analysis results and determines more profound patterns relating to vulnerabilities. The model is trained using datasets of secure and vulnerable smart contracts using supervised learning, classification algorithms, or deep neural networks. It trains itself to get the finer details of the code structure and the behavior that can be missed using conventional techniques. This element enhances flexibility and allows the system to pick up any emerging threats that are not covered by the established rules.

3.2.6. Vulnerability Classification

At this phase, the results of the analyses performed in the previous stage, the dynamic analysis and the machine learning model are merged to classify the smart contract. The system finds

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out whether the contract is susceptible or resistant depending on aggregated evidence and confidence scores. It can be a process of severity assessment, vulnerability categorization, and prioritization of risks. It also makes sure that the final decision is holistic and that it takes into consideration numerous points of analysis.

3.2.7. Output: Secure / Vulnerable Contract

The end product of the system is the result of classification, which shows the smart contract as either secure or vulnerable. In addition to this choice, the system can also include comprehensive reports on the vulnerabilities that are identified and the level of their severity, as well as the possible recommendations on the remediation. This output helps the developers, auditors, and stakeholders to interpret the security posture of the contract and undertake the right corrective measures before deployment.

3.3. Feature Extraction

3.3.1. Opcode Sequences

Opcode sequences denote the low-level code that the smart contract runs on the blockchain virtual machine. Under this method, the generated bytecode of the contract is disassembled into a series of operation codes (opcodes), each having a particular action, e.g. arithmetic operations, storage access, or modification of control flow. These sequences allow us to have a closer look at the behavior of the contract on execution. Through opcode patterns, the system is able to detect suspicious combination of instructions or known vulnerability signatures. The ability to transform these sequences into numerical vectors allows machine learning models to process and learn execution-level behavior effectively.

3.3.2. Control Flow Graphs

Control Flow Graphs (CFGs) are a representation of the logical execution in a smart contract, where functions and instructions are represented as nodes, and the execution paths as edges. This graphical representation assists in the understanding the way in which various elements of the contract can interact with one another and how execution can switch in and out between states. CFGs are especially effective to detect complicated vulnerabilities like infinite loops, unreachable code, or inappropriate branching conditions. CFGs enable analysis models to identify abnormal or dangerous execution paths that might not be obvious by inspection of the linear code, by encoding the structural and flow-related information into numerical features.

3.3.3. Abstract Syntax Trees

ASTs give us a hierarchical structure of the source code of the smart contract, with a node representing a syntactic construct, e.g. variables, operators, or control statements. ASTs maintain the structural and semantic connections between the code, thus are very helpful to be deeply analyzed. With the help of AST-based feature extraction, key patterns of feature definitions, inheritance and data structure can be recognized. Such trees can be commonly converted to vectorized forms or

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embeddings, allowing machine learning and deep learning models to learn high-level code semantics and can identify subtle vulnerabilities that are hard to find using more conventional approaches.

3.4. Machine Learning Models

Fig 4 - Machine Learning Models

3.4.1. Supervised Learning

Supervised learning methods are popular in categorizing smart contracts using known vulnerabilities through model training on labeled data. The examples of secure and vulnerable contracts are presented in these datasets, allowing the models to learn distinguishing patterns and features. After the training, the models are able to make precise forecasts of the presence of known security concerns in a new smart contract. This method is very useful in identifying the vulnerabilities that have been previously determined and also offers quality classification performance where there is enough and good quality labeled data.

3.4.2. Support Vector Machines (SVM)

The support vector machines (SVM) are the effective classification algorithms which operate on the basis of establishing the best hyperplane to classify the data into various categories. In analysing smart contracts, SVMs are applied to identify vulnerable and non-vulnerable contracts with respect to features extracted as opcodes sequences or structural patterns. They work especially well with high-dimensional spaces and they are able to work with complex decision boundaries with the help of kernel functions. SVMs can however be sensitive to parameter tuning and do not scale very well with large datasets.

3.4.3. Random Forest

Random Forest is an ensemble machine learning strategy that integrates a series of decision trees to enhance the accuracy and the strength of classification. The trees are trained individually on a portion of the data and the ultimate prediction is achieved by the majority vote of all trees. When applied to the analysis of smart contracts, Random Forest models can serve to work with different sets of features and minimize overfitting. They also give the information on the importance of

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features, which allows finding out what aspects of the contract may bring the most vulnerabilities. Their benefits are that they can be computationally costly as the number of trees grows.

3.4.4. Neural Networks

Neural Networks, especially deep learning models are very useful at encoding complex trends in smart contract data. These models are composed of several layers of interconnected neurons that acquire hierarchical representations of features. Neural networks can be used in vulnerability detection in structured inputs like ASTs or ordered data sequences like opcode sequences to detect subtle and hidden patterns. They are also good in identifying known and new vulnerabilities due to their generalization capabilities. Nevertheless, they need massive datasets and huge amounts of computational power to be trained and their decision-making process can be hard to understand.

3.4.5. Unsupervised Learning

Unsupervised learning is applied in cases where the labeled data is not available or in limited amounts, and it concentrates on discovering hidden patterns or anomalies in smart contract datasets. These methods are not based on preset labels but rather are used to cluster similar data points or indicate anomalies in normal behavior. Unsupervised learning is especially applicable in smart contract analysis to find new or unfamiliar vulnerabilities by detecting an abnormal code structure or execution behavior that does not apply to normal contracts.

3.4.6. K-Means Clustering

K-Means Clustering is a widely used unsupervised learning algorithm to cluster data into a specified number of clusters (based on similarity). It also clusters contracts in smart contract analysis with similar characteristics, which allows the identification of outliers that can be potential vulnerabilities. Through the cluster distributions, security analysts are able to identify abnormal patterns or unusual behaviors that should be investigated. Although K-Means is easy to use and effective, it requires the selection of the number of clusters, and it can be ineffective with non-linear or complex data distributions.

3.4.7. Autoencoders

Autoencoders are a neural network that performs unsupervised learning, which especially works well in anomaly detection. They operate by encoding input data into a compressed form and then reassembling it to its original form. In the process, the model is trained on the regular trends of smart contract data. In the case of a contract with atypical or abnormal characteristics being processed, the error of reconstruction is larger, which indicates a possible vulnerability. Autoencoders are very useful in the detection of new threat that has never been detected before, but it is very sensitive to training and input data quality.

3.5. Mathematical Model

The problem of vulnerability classification in smart contract analysis could be presented in the form of a mathematical function in the simple form as f of x equals y. In this definition, x is the

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extracted feature vector of the smart contract, which can consist of sequence of opcodes, patterns of control flows, and representations of abstract syntax trees. The prediction y is the vulnerability prediction, which could be secure or vulnerable, or even more specific vulnerabilities such as reentrancy or overflow errors. The function f is the machine learning model which will be used to predict the output class given the input features according to the patterns that have been learnt on the training data. In order to make sure that the model makes correct predictions, a loss function is employed to gauge the difference between the predicted output and the actual label. Simply, the loss function is used to estimate the distance between the model prediction and the actual classification. In classification issues, loss functions that are often used are cross-entropy loss and mean squared error, depending on the model type. The aim of the training process is to reduce the value of this loss in order to have the predictions as near to the actual results as possible. This is done by use of optimization methods like gradient descent whereby the model parameters are continuously changed in order to minimize errors. The loss function is an important aspect of enhancing model reliability and accuracy in the smart contract vulnerability detection context. The less the loss value the better, as it implies that the model is capable of making a clear distinction between safe and unsafe contracts. Moreover, regularization methods can also be added to the loss to avoid overfitting and improve the generalization to unobserved data. Altogether, this mathematical implementation offers an organized approach to automating vulnerability classification and allows introducing sophisticated machine learning methods into smart contract security analysis.

3.6. Algorithm: AI-Based Smart Contract Analysis

3.6.1. Input Smart Contract Code

The input of the algorithm is the smart contract code, which can be in high-level languages like Solidity or in compiled form of a binary code. This step is the basis of the analysis process, during which the contract is gathered by the developers or blockchain platforms. It is also necessary to make sure that the input is complete and properly formatted, and any missing elements or inconsistencies may influence the further analysis processes and cause erroneous outcomes.

3.6.2. Perform Preprocessing

At the preprocessing phase, the input smart contract undergoes cleaning and standardization to be ready to undergo analysis. This involves the elimination of redundant information, refactoring of code structure, and transformation into other intermediate representations such as tokenized sequences or syntax trees. Preprocessing also preconditions compatibility with analysis tools and machine learning models, enhancing efficiency and consistency in various contracts.

3.6.3. Extract Features

The feature extraction process entails converting the processed smart contract in meaningful numerical forms that may be utilized by analysis models. Characteristics like opcode sequences, control flow patterns and abstract syntax structures are recognized and coded. These features

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represent structural as well as behavioral traits of the contract making it easy to identify the vulnerabilities when the data undergoes analysis and learning models.

3.6.4. Apply Static Analysis

In the process of the static analysis, the algorithm analyses the contract but does not execute the contract to determine the known vulnerabilities based on predefined rules and patterns. This step assists in the identification of common bugs like reentrancy attacks, arithmetic bugs, and access control bugs. The information presented by a static analysis is fast and effective and enables one to identify possible risks before runtime analysis.

3.6.5. Execute Dynamic Analysis

Dynamic analysis is the process of running the smart contract in a regulated or simulated environment to trace its behavior at runtime. The algorithm exercises different input cases and observes transitions of states, calls to functions, and communications with other contracts. It is a step towards determining vulnerabilities that are only revealed during execution such as unexpected behavior or runtime exceptions to have a better insight into contract performance.

3.6.6. Train Machine Learning Model

During this phase, a machine learning model is given instructions to be trained on labeled sets of legitimate and insecure smart contracts. The features that have been extracted are used as the input to the model which is then able to learn the patterns related to various forms of vulnerabilities. Training entails the process of adjusting model parameters to reduce prediction error so as to allow the system to extrapolate and make correct predictions on unseen contracts.

3.6.7. Classify Vulnerabilities

The model is then applied to categorize the analyzed smart contract by its features and observed behavior after training. The algorithm will either tell that the contract is secure or vulnerable and it might also classify the nature of vulnerability. This step in classification combines the results of the traditional methods of analyzing the data with the results of the machine learning prediction to create a complete analysis.

3.6.8. Output Results

The last phase of the algorithm produces the results of the output, which include the classification result and a detailed view. The system can inform that the smart contract is either secure or vulnerable and can contain data about identified problems, level of severity and suggested solutions. This output will help developers and auditors to enhance the security of contracts and the safety of deployment on blockchain platforms.

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4. RESULTS AND DISCUSSION

4.1. Performance Metrics

Performance metrics are important in assessing the effectiveness of the proposed AI-based smart contract analysis system since it has quantitative values of the ability of the model to detect vulnerabilities. The simplest measure is accuracy, the percentage of correctly classified smart contracts (secure and vulnerable) of the overall sample size. As much as accuracy provides a general picture of the model performance it is not always reliable when the dataset is skewed in some instances like when the vulnerable contracts are very few compared to those that are secure. To overcome this shortcoming, the accuracy of positive prediction is measured by precision. It shows the percentage of contracts that are vulnerable that are really vulnerable. With high precision, it implies that the model generates lower false positives which is valuable in terms of lowering the number of unnecessary alerts and saving time in conducting manual audits. Conversely, recall (or sensitivity) is used to assess the capability of the model to select all the real vulnerable contracts. The large recall value would mean that the majority of the vulnerabilities would be identified, thus reducing the chances of missing out on essential security vulnerabilities. Nevertheless, recall can be enhanced at the expense of false positives, and this poses a trade-off between precision and recall. The F1-Score is employed to strike a balance between these two metrics, and it is the harmonic mean of the recall and precision. It gives one, overarching evaluation of model performance particularly in cases where there is an imbalanced dataset. The F1-score is high, which means that the model has a good balance between the correct identification of vulnerabilities and the reduction of the false classifications. Collectively, these measures provide an integrated assessment scheme, which allows researchers and developers to evaluate and streamline the operations of smart contract vulnerability detectors efficiently.

4.2. Vulnerability Detection Results

Table 1: Vulnerability Detection Results

Vulnerability Type	Detection Rate (%)
Reentrancy Attack	92%
Integer Overflow	88%
Gas Limit Issues	85%
Timestamp Dependency	83%
Denial of Service	87%

4.2.1. Reentrancy Attack (92%)

The proposed system is shown to have a high reentrancy attack detection rate of 92% that is one of the most important vulnerabilities in smart contracts. This kind of attack happens when a contract is used to allow external repeated calls before updating its internal state, and attackers can utilize the contract and get money back several times. The combination of the static analysis, dynamic monitoring, and the AI-based pattern recognition is effective in the detection of the reentrancy patterns as the detection accuracy is high. The high performance is an indication that the system can support intricate execution processes and protect financial transactions.

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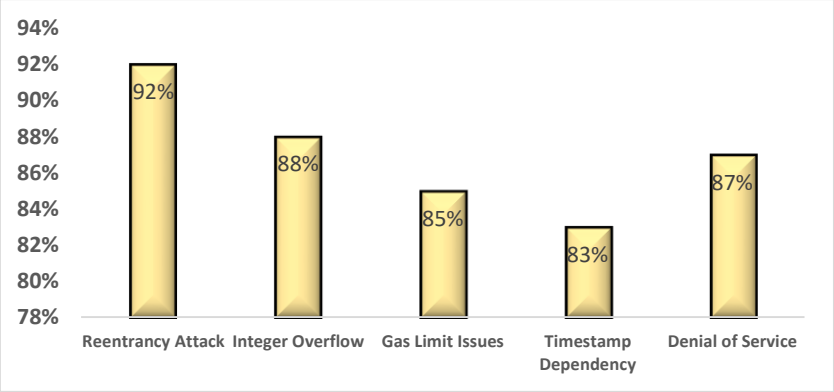

Fig 5 - Vulnerability Detection Results

4.2.2. Integer Overflow (88%)

In the case of integer overflow vulnerabilities, the system has a detection rate of 88% indicating its capability to detect arithmetic related problems. The integer overflow is upon the value being beyond its maximum value, which causes some unanticipated behavior or wrong calculations. The model effectively identifies these vulnerabilities through the analysis of opcode sequences, arithmetic operations in the contract. This rate is slightly lower than the reentrancy detection, but it is still an indicator of a decent performance, given the sensitivity of arithmetic bugs in smart contract logic.

4.2.3. Gas Limit Issues (85%)

The system achieves 85 percent gas limit issues detection, which occur when contracts use too much of the computational resources or fail because they were not assigned enough gas. These problems may interfere with the execution of contracts, and result in unfinished transactions or denial of service conditions. Through dynamic analysis and runtime monitoring, the system is able to find inefficient loops, recursive calls, and resource-consuming operations. Although the detection rate is average, it shows that the system is capable of analyzing performance related vulnerabilities which can often be contingent on the conditions of execution.

4.2.4. Timestamp Dependency (83%)

The accuracy of identifying timestamp dependency vulnerabilities stands at 83, which implies that the system can identify the use of block timestamps in making important decisions. Miners being unable to control timestamps well can exploit such dependencies to manipulate the outcome of contracts. The detection is done by analyzing conditional statements and finding a pattern in which timestamps are used to affect logic. The detection rate is a little smaller than those of other vulnerabilities, but still indicates the ability of the model to model contextual and environment-specific risks.

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4.3. Discussion

The experimental findings are clear to show that AI-based solutions are strongly effective to increase the effectiveness of smart contract vulnerabilities detection compared to when using conventional analysis tools. Incorporating machine learning methods with both dynamic and static analysis, the proposed hybrid model can identify the known vulnerability patterns, as well as complex, never observed before actions. This combination enables the system to break the constraints of rule-based tools that frequently cannot withstand high false positive rates and lack flexibility. The higher detection rates of the various vulnerability types testify to the fact that the model is capable of generalization and offers more accurate security tests on smart contracts. The possibility to use complementary techniques is one of the major strengths of the hybrid approach. Statics rule analysis can affordably detect known vulnerabilities and dynamic analysis can give information about the behavior at runtime. Machine learning further improves detection by being able to detect subtle patterns and correlations in the data that struggle to be detected manually by rules. Due to this, the system attains greater total accuracy and a better balance of precision and recall and is therefore appropriate in real-life applications where both detection accuracy and efficiency are vital. Although these benefits are there, there are still a number of challenges. The imbalance of the datasets is also a significant problem, in which there is usually a higher amount of safe contracts than unsafe contracts. Such an imbalance may skew the model and minimize its detection capabilities of less common vulnerabilities. Also, machine learning models (especially deep learning methods) are not always interpretable, and it is not always easy to tell why a particular contract can be considered vulnerable. This invisibility may constrain developer and auditor trust and acceptance. The need to tackle these issues by enhancing data gathering, balanced training, and being able to explain AI-based smart contract analysis systems will be critical to the further development of these systems.

5. CONCLUSION

This work provides a detailed research on AI and smart contract analysis to secure digital transactions, which has become increasingly significant in blockchain security. The suggested framework is a successful combination of the method of static analysis, dynamic analysis and machine learning to design a powerful and scalable vulnerability detection system. Through these complementary strategies, the framework will deal with the limitations inherent in the traditional approaches, including high false positives, non-adaptable, and incapability of identifying complex or emerging vulnerabilities. The use of static analysis allows the identification of known problems during pre-execution rule-based inspection, and dynamic analysis allows the capture of runtime behaviors, which are frequently overlooked in pre-execution analysis. Machine learning further reinforces the system, as it allows the system to provide insights that are based on data and recognize patterns, which makes it possible to identify known and previously unknown threats. The experimental outcomes prove that the hybrid model greatly enhances performance in terms of accuracy, precision, recall, and general detection rates in the case of most of the types of vulnerabilities, such as reentrancy attacks, integer overflows, gas-related problems, timestamp dependencies, and denial-of-service threats. These results verify that AI-based solutions may offer

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superior and more trustworthy security evaluations than the traditional ones. Additionally, the fact that the system can be applied in other contract structures and identify the minor vulnerabilities points to the possibility of its use in the real world of blockchain ecosystems. Although there are such advances, the study also admits some challenges that should be overcome. Such issues as the imbalance of datasets can influence the performance of the model, especially with the detection of rare vulnerabilities, and the absence of interpretability in complex machine learning models can reduce transparency and user trust. These are the challenges that make it necessary to conduct additional studies and development to be able to guarantee the accuracy and explainability of AI-based solutions. Further research should consider improving the framework with explainable AI methods that will offer more transparent explanations of the model decisions and make them more user-friendly to the developers and auditors. Moreover, the real-time monitoring systems will be integrated to conduct a constant analysis of smart contracts post-implementation to maintain the protection against dynamic threats. In general, this work highlights the revolutionary nature of artificial intelligence in the development of smart contract security and preconditions the future of the secure and reliable system of digital transactions.

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