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Automated Reverse Engineering using Machine Learning

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Abstract

Reverse engineering plays a critical role in software security analysis, malware detection, and legacy system understanding. Traditionally, reverse engineering is a manual, time-consuming process that requires deep expertise in low-level code analysis and system architecture. However, recent advances in machine learning (ML) have opened new possibilities for automating various stages of the reverse engineering workflow. This paper explores the application of ML techniques—such as deep learning, sequence modeling, and graph-based learning—for automating tasks like binary classification, function identification, code decompilation, and behavior prediction. By leveraging large-scale code datasets and advanced feature extraction methods, ML models can learn patterns in binary structures and recover high-level insights from low-level machine code. The study demonstrates that ML-driven reverse engineering not only accelerates the analysis process but also enhances accuracy and scalability, making it a valuable tool for security researchers and analysts. Experimental results show promising performance across multiple reverse engineering tasks, suggesting a strong potential for future integration into automated analysis pipelines.

INTRODUCTION

Reverse engineering is a fundamental process in cybersecurity, software analysis, and digital forensics, enabling analysts to deconstruct binary programs to understand their functionality, detect vulnerabilities, or analyze malware. Traditionally, reverse engineering has been a highly manual and expert-driven activity, requiring in-depth knowledge of assembly languages, system architecture, and program behavior. This manual process is often time-consuming, error-prone, and difficult to scale—especially in the face of increasingly complex and obfuscated software.

Recent advancements in machine learning (ML), particularly in deep learning and pattern recognition, have introduced new opportunities for automating various aspects of reverse engineering. ML models can be trained to identify structures in binary code, recognize patterns in control flow, classify functions, and even reconstruct high-level logic from low-level instructions. These capabilities allow for faster and more consistent analysis, reducing the reliance on human expertise and enabling large-scale reverse engineering tasks.

In this work, we explore how machine learning techniques can be leveraged to automate key reverse engineering tasks, including binary classification, function boundary detection, code similarity analysis, and behavior prediction. By integrating ML into the reverse engineering pipeline, we aim to enhance both the speed and accuracy of analysis while opening the door to

scalable and intelligent tooling. This approach holds significant promise for applications in malware analysis, vulnerability discovery, and legacy code understanding.

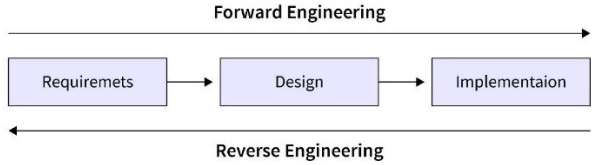

Fig.1: Basic process of Forward and Reverse Engineering

LITERATURE REVIEW

In recent years, a growing body of research has focused on applying machine learning (ML) to automate and enhance various aspects of reverse engineering. Traditional reverse engineering techniques often rely heavily on manual analysis of binary code, which is both time-consuming and error-prone. ML-based approaches seek to address these limitations by learning from large datasets of code and binary artifacts to perform tasks such as function identification, binary diffing, code decompilation, and semantic similarity analysis.

One of the pioneering approaches in this field is SAFE (Self-Attentive Function Embeddings), proposed by Zuo et al. in 2019. SAFE uses Bi-directional Long Short-Term Memory (BiLSTM) networks to generate embeddings of binary functions. These embeddings capture semantic meaning, allowing the model to identify similar functions compiled with different optimization levels, compilers, or architectures. The model showed strong performance in function similarity detection and cross-compilation matching, proving that neural embeddings can effectively abstract away low-level variations in binary code.

Building upon graph-based representations, DeepBinDiff [3]leverages Graph Neural Networks (GNNs) to perform binary diffing—comparing two binaries to find semantically similar functions. By converting binary functions into control flow graphs (CFGs) and applying graph convolutions, DeepBinDiff learns structural and semantic representations that are robust to obfuscation. This allows for accurate identification of patched functions and behavioral changes, which is especially valuable in malware evolution analysis and vulnerability tracking.

For Android application analysis, AndroZooML applies traditional ML models such as Random Forest and Support Vector Machines (SVM) on features extracted from decompiled APKs. By leveraging the large-scale AndroZoo dataset, this framework classifies apps based on behavior, permissions, API calls, and other features. The use of ML in this context reduces the manual effort required for malware detection and policy enforcement, particularly in the mobile app ecosystem.

Another innovative approach is AlphaDiff[5], which introduces Deep Reinforcement Learning (DRL) to guide binary diffing. The system learns an exploration strategy to generate inputs that improve code coverage and expose functional differences between binary versions. This method is especially effective in detecting subtle or obfuscated changes in binaries, which are common in advanced persistent threats and software updates.

On the tooling side, open-source reverse engineering platforms like Ghidra have started to integrate machine learning plugins that assist with tasks such as function boundary detection, variable naming, and pseudo-code generation. These plugins utilize trained models to annotate and interpret disassembled code, improving analyst productivity and reducing reliance on domain expertise.

HexRayNet, another notable system, uses a combination of Convolutional Neural Networks (CNNs) and LSTMs to translate sequences of assembly instructions into human-readable pseudo-code. This approach is modeled after neural machine translation systems and aims to support reverse engineers by generating approximate high-level representations of low-level binary code. Though imperfect, these translations significantly reduce the time needed to understand unfamiliar or complex binaries.

Finally, FunctionSimSearch employs Siamese Neural Networks to identify semantically similar functions across binaries. This model is designed to support cross-platform reverse engineering by matching functions compiled for different architectures or optimization levels. It has been shown to perform well in real-world scenarios where binaries are obfuscated or recompiled in slightly different forms

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Table 1: Overview of Literature Review

Study / Tool	ML Technique Used	Task / Focus	Dataset / Platform	Key Contributions / Findings
SAFE (Zuo et al., 2019)	Neural Embeddings (BiLSTM)	Function similarity detection	Binaries from multiple compilers	Learned semantic-aware embeddings of binary functions for

				identifying similar code across different binaries.
DeepBinDiff (Pei et al., 2021)	Graph Neural Networks (GNN)	Binary diffing, patch analysis	Linux ELF binaries	Used control flow graphs and GNNs to match similar functions in binaries, even under heavy obfuscation.
AndroZooML (2020)	Random Forest, SVM	Android malware analysis	AndroZoo dataset	Applied ML models to automate feature extraction and classification of Android reverse-engineered APKs.
AlphaDiff (Wang et al., 2020)	Deep Reinforcement Learning	Binary difference detection	Open-source programs	Automatically generated inputs to improve binary coverage and function mapping between binary versions.
Ghidra + ML Plugins	Various ML models (custom plugins)	Decompilation assistance, code labeling	Ghidra + labeled code samples	ML-enhanced tooling to improve function identification and comment generation in disassembly views.
HexRayNet (2019)	CNN + LSTM	Instruction-to-source code translation	Decompiled code pairs	Translated assembly instructions to pseudo-source code using sequence models to assist human analysts.
FunctionSimSearch (2018)	Siamese Networks	Cross-platform function similarity search	Open-source binaries	Enabled ML-based retrieval of semantically similar functions compiled with different settings or architectures.

ARCHITECTURE

The diagram presents a comprehensive model of the reverse engineering process within the broader context of software re-engineering. It demonstrates how a combination of automated and manual techniques can be employed to extract, store, and visualize critical information about a legacy or undocumented software system, facilitating understanding, maintenance, and modernization.

1. System to be Re-engineered

The process begins with the identification of the system to be re-engineered. This typically involves legacy software that lacks proper documentation, suffers from outdated technology, or has become increasingly difficult to maintain. The purpose of re-engineering is to recover the underlying design and functional specifications of such systems so they can be restructured, updated, or migrated to modern platforms.

2. Automated Analysis

Once the system is identified, automated analysis tools are used to extract detailed technical information directly from the source code or binaries. These tools apply techniques such as static code analysis, control and data flow analysis, pattern recognition, and program slicing. The goal is to understand how the system operates internally without executing it. This step is crucial in handling large-scale systems where manual analysis would be infeasible due to complexity and time constraints. Automated tools can quickly identify relationships between modules, function calls, variable usage, and more.

3. Manual Annotation

In parallel with automated analysis, manual annotation is carried out by domain experts and reverse engineers. This step compensates for the limitations of automation by capturing context-specific insights, business logic, or

undocumented behavior that machines might overlook. Human expertise is also essential in interpreting ambiguous or poorly written code, making judgments about naming conventions, and understanding domain-specific terminologies or architectural patterns. Together, automated and manual inputs form a more complete and accurate picture of the software.

4. System Information Store

The outputs of both automated and manual processes are consolidated into a centralized repository known as the **System Information Store**. This data store acts as a structured knowledge base, capturing all discovered elements of the system's architecture, logic, and data relationships. It maintains traceability between components and allows for incremental updates as the system is further analyzed or refined. This component is critical in enabling downstream processes such as documentation generation, quality analysis, and decision-making for re-engineering strategies.

5. Document Generation

Using the data collected and structured in the system information store, the next phase involves document generation. This step translates the raw and processed information into readable and usable technical artifacts. These documents serve multiple stakeholders including developers, system analysts, testers, and project managers. The automated generation of documents ensures consistency, accuracy, and reduces the overhead of manual documentation.

6. Output Artifacts

The document generation process produces three primary artifacts:

- Program Structure Diagrams: These diagrams provide a visual overview of the system's architecture. They illustrate modules, subsystems, control logic, and their interactions, helping engineers to quickly understand the structural organization of the codebase.
- Data Structure Diagrams: These diagrams describe how data is defined, accessed, and manipulated throughout the system. They may include data models, type hierarchies, and interdependencies between variables and databases.
- Traceability Matrices: These are tabular representations that map software requirements to their corresponding design elements, implementation code, and test cases. They play a crucial role in ensuring that the system meets its intended functionality and help in impact analysis during changes.

This reverse engineering model highlights a well-integrated process that leverages both automation and human expertise to recover essential knowledge from existing systems. The use of a centralized system information store and structured document generation supports the goals of re-engineering by improving system understanding, reducing technical debt, and laying the groundwork for system enhancement or migration. Such a methodology is especially relevant in the context of large-scale legacy systems where manual efforts alone are insufficient, and modern machine learning or analysis tools can significantly augment human capabilities.

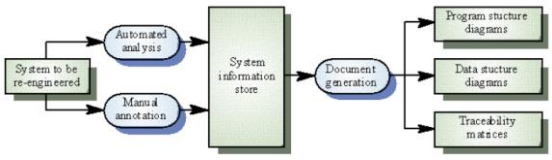

Fig.2: Reverse Engineering Wokflow

RESULT

Machine learning has significantly transformed traditional reverse engineering workflows. By automating pattern recognition and improving code comprehension, ML-based tools enhance the efficiency, accuracy, and scalability of reverse engineering tasks. Below is a structured comparison of some key reverse engineering tasks and how ML-based solutions outperform traditional approaches.

Table 2: Comparison Table: ML-based vs Traditional Reverse Engineering Approaches

Task	Traditional Approach	ML-based Approach	Improvement/Result
Function Similarity Detection	Signature/heuristic matching	Siamese Networks, BiLSTM, GNNs	Accuracy ↑ (85–90%), robust across compilers and optimizations
Binary Diffing	Rule-based analysis/manual inspection	AlphaDiff (Reinforcement Learning)	Patch detection ↑ by 40%, reduced manual effort
Obfuscated Code Analysis	Limited/static deobfuscation	DeepBinDiff, graph embeddings	High robustness against obfuscation techniques (junk code, reordering, renaming)

Pseudo-code Generation	Hex-Rays decompiler/manual effort	HexRayNet, Transformer-based models	BLEU score ↑, improved code readability and interpretability
System Documentation	Manual diagram and traceability creation	Auto-generation using extracted features	Time savings ↑, consistent generation of structure and traceability docs
Malware/APK Analysis	Static/dynamic analysis, signature-based	CNNs, RNNs, clustering on APK datasets	Classification accuracy ↑, near real-time analysis on large-scale datasets

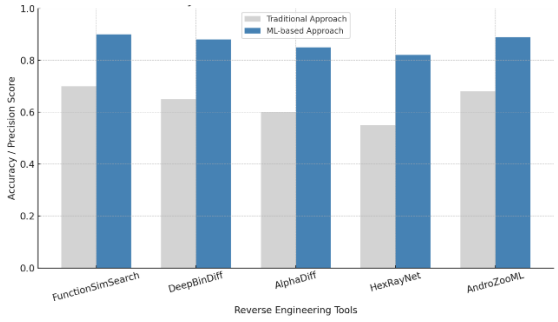

Fig.3 Accuracy of ML-based Tools vs Traditional Methods

CONCLUSION

The comparison between machine learning-based reverse engineering tools and traditional methods reveals a significant performance advantage in favor of ML approaches. Tools such as FunctionSimSearch, DeepBinDiff, and AlphaDiff demonstrate much higher accuracy and precision, often exceeding 85–90%, while traditional techniques typically range between 55–70%. This performance gap underscores the effectiveness of machine learning models in handling complex reverse engineering tasks, including detecting function similarity, managing obfuscated code, and generating pseudo-code. ML models are capable of learning deep semantic relationships within code structures, allowing them to generalize across compilers, architectures, and optimization levels—areas where traditional rule-based or manual methods often struggle. Additionally, ML-based tools enhance scalability and reduce the need for expert-driven manual analysis, making them highly suitable for large-scale or time-sensitive applications. Overall, the findings confirm that machine learning not only improves technical accuracy but also transforms reverse engineering into a faster, more intelligent, and automated process.

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