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Original Article

Privacy-Preserving ML for Analyzing Usage Telemetry to Improve Software Reliability without Exposing User Data

Sanjay Verma[1], Naveen Kumar[2]

[1]*Operations Manager, HCL Technologies, India.*

[2]*Product Manager, Zoho Corporation, India.*

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ABSTRACT

Ensuring software reliability is critical in modern applications, yet analyzing usage telemetry often involves sensitive user data, raising significant privacy concerns. This paper proposes a privacy-preserving machine learning framework for analyzing usage telemetry to improve software reliability without exposing individual user information. We explore techniques such as federated learning and differential privacy to enable collaborative model training while keeping raw data localized. Our approach leverages telemetry data to predict software failures, detect anomalies, and identify reliability hotspots. Experimental results demonstrate that our framework achieves competitive predictive performance while maintaining strong privacy guarantees, offering a practical solution for privacy-aware software reliability analysis.

KEYWORDS

Privacy-Preserving Machine Learning, Usage Telemetry, Software Reliability, Federated Learning, Differential Privacy, Anomaly Detection, Privacy-Aware Software Engineering.

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1. INTRODUCTION

1.1. Background: Importance of Software Reliability and Usage Telemetry

Software reliability is a critical attribute of any modern software system, as failures can lead to significant economic loss, reputational damage, or even safety hazards in mission-critical applications. Over the years, the collection and analysis of usage telemetry has become a vital practice for understanding software behavior in real-world environments. Usage telemetry refers to the systematic gathering of runtime data from end-user systems, including metrics like application crashes, execution traces, performance counters, resource utilization, and user interaction patterns. By analyzing this telemetry, software engineers can identify frequently failing modules, detect performance bottlenecks, and uncover latent defects that might not manifest during testing. Telemetry data thus provides a rich source of information for continuous improvement of software reliability, enabling predictive maintenance, informed bug fixing, and proactive enhancement of system stability.

1.2. Challenges: Privacy Concerns in Telemetry Collection and Analysis

While telemetry data is invaluable for improving software reliability, it often contains sensitive information about end users, including behavioral patterns, interaction sequences, and potentially personally identifiable information (PII). Collecting and analyzing such data raises significant privacy concerns, as improper handling could expose user data to unauthorized access, regulatory non-compliance, or even misuse. Conventional approaches often rely on centralizing telemetry data for analysis, which increases the risk of data leaks and privacy breaches. Additionally, there are challenges in anonymizing telemetry effectively, as simple masking or aggregation techniques may reduce the utility of data or fail to provide sufficient privacy guarantees. This presents a trade-off between leveraging rich telemetry for software improvement and protecting user privacy, a challenge that traditional reliability analysis methods often cannot address.

1.3. Motivation: Need for ML-Based Approaches that Preserve Privacy While Improving Software Reliability

To address these challenges, there is a growing motivation to adopt machine learning (ML) approaches that can analyze usage telemetry effectively while ensuring that individual user data remains private. ML models have the capability to detect complex patterns, predict failures, and identify reliability hotspots in software systems, often outperforming rule-based or statistical approaches. However, the challenge lies in applying ML without centralizing sensitive telemetry, which could compromise privacy. Privacy-preserving ML techniques, such as federated learning, differential privacy, and secure multi-party computation, provide a way to build predictive models on distributed telemetry data while keeping raw user data local and confidential. These approaches enable the software industry to harness the power of ML for reliability enhancement without violating user trust or regulatory standards.

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1.4. Problem Statement: How to Leverage Usage Telemetry without Exposing Sensitive User Data

The central problem addressed in this research is how to utilize detailed telemetry data for improving software reliability while guaranteeing user privacy. Traditional ML pipelines require centralized access to raw data, which conflicts with privacy requirements, especially in domains subject to strict regulations such as healthcare, finance, or IoT systems. The challenge is to design a framework where telemetry data can contribute to the predictive modeling of failures, anomaly detection, and reliability assessment without ever leaving the user's environment in raw form. This problem requires a careful combination of ML techniques and privacy-preserving methods, balancing model performance with rigorous privacy guarantees.

1.5. Contributions of this Paper

This paper makes several contributions to the field of privacy-aware software reliability analysis. First, it proposes a privacy-preserving ML framework that integrates federated learning and differential privacy for analyzing usage telemetry data. Second, it demonstrates how the framework can be applied to predict software failures and detect anomalies without exposing sensitive user information. Third, the paper evaluates the trade-offs between predictive performance, privacy protection, and computational efficiency, providing empirical evidence of the framework's practicality. Finally, it provides insights into the potential integration of such privacy-preserving approaches into software development and operations, offering guidance for industry adoption.

2. RELATED WORK

2.1. Overview of Usage Telemetry in Software Reliability Studies

Usage telemetry has long been used in software engineering to enhance reliability and maintainability. Historically, telemetry was collected primarily for monitoring system performance and detecting runtime errors, such as crashes or memory leaks. In recent years, telemetry data has been leveraged for predictive reliability modeling, where historical telemetry is used to forecast potential failures, identify high-risk components, and prioritize maintenance activities. Studies have shown that telemetry-based approaches can significantly improve software quality by providing actionable insights derived from real-world usage, supplementing traditional testing and static analysis methods. Telemetry analysis enables the identification of patterns that would otherwise remain hidden in manual testing or development logs, making it an essential tool for modern software systems.

2.2. Privacy-Preserving Techniques in ML (E.G., Federated Learning, Differential Privacy, Homomorphic Encryption)

In response to growing privacy concerns, a range of privacy-preserving ML techniques have been developed. Federated learning allows multiple clients to collaboratively train a machine learning model without sharing their raw data; only model updates are aggregated, reducing privacy risks**.** Differential privacy introduces carefully calibrated noise into data or model parameters, ensuring that individual contributions cannot be inferred while maintaining overall analytical utility. Homomorphic encryption enables computations on encrypted data, allowing ML models to operate

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on sensitive inputs without ever decrypting them. These techniques provide mechanisms to reconcile the tension between data utility and privacy, making it feasible to apply ML to sensitive telemetry data in real-world software environments.

2.3. ML Approaches for Reliability Prediction and Anomaly Detection in Software Systems

Machine learning has been increasingly applied to software reliability tasks, including failure prediction, fault localization, and anomaly detection. Supervised learning models, such as random forests and neural networks, can be trained to classify software modules as likely to fail or to regress, based on historical telemetry and code metrics. Unsupervised and semi-supervised methods, such as clustering and autoencoders, are used for detecting anomalies in runtime behavior or performance metrics. These ML approaches outperform traditional rule-based methods by capturing complex temporal and spatial dependencies in telemetry, offering more accurate and proactive reliability management.

2.4. Gaps in Existing Research

Despite these advances, existing studies often assume centralized access to telemetry data, which creates privacy risks and limits applicability in sensitive domains. Few works address the integration of privacy-preserving techniques with ML-based reliability modeling, and empirical evaluations of the trade-offs between model accuracy, privacy protection, and system performance remain limited. There is also a lack of frameworks that combine multiple privacy mechanisms (e.g., federated learning with differential privacy) specifically for software telemetry, leaving a gap for approaches that are both practically deployable and privacy-aware. This research aims to address these gaps by proposing a holistic framework for privacy-preserving telemetry analysis.

3. METHODOLOGY

3.1. Data Collection: Types of Telemetry Data (Logs, Metrics, Usage Patterns)

The foundation of any software reliability analysis framework is data collection, which involves gathering comprehensive telemetry from deployed software systems. Telemetry data typically includes logs, such as error logs, crash reports, and execution traces, which provide a chronological record of software behavior at runtime. It also encompasses performance metrics, including CPU and memory utilization, response times, throughput, and network latency, which reflect the operational health of the system. Additionally, usage patterns—such as user interactions, feature access frequency, and session durations—offer insights into how the software is utilized under real-world conditions. Collectively, these data types enable the identification of latent defects, anomalous behavior, and reliability hotspots. In a privacy-preserving context, data collection must be structured so that sensitive user information is either anonymized or kept local to the client device, ensuring that no personally identifiable information is transmitted during analysis.

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3.2. Privacy-Preserving Techniques

3.2.1. Federated Learning

Federated learning is a decentralized approach to model training where multiple clients collaboratively train a shared machine learning model without sending raw data to a central server. Each client computes model updates locally based on its private telemetry data, and only these updates are transmitted for aggregation. This approach allows the system to benefit from diverse, real-world usage patterns across multiple devices while maintaining strict data locality, ensuring that user telemetry remains confidential. Federated learning is particularly suitable for large-scale software deployments where telemetry is distributed across numerous user devices or enterprise systems.

3.2.2. Differential Privacy

Differential privacy is a mathematical framework that introduces controlled noise into data or model updates to prevent the disclosure of individual-level information. By carefully calibrating the noise, the aggregated model can provide accurate predictions while obfuscating the contribution of any single user's data. When applied to telemetry, differential privacy ensures that even if an adversary gains access to the trained model, they cannot infer details about any individual user's behavior, making it a critical component in privacy-preserving software reliability analysis.

3.2.3. Secure Multi-Party Computation

Secure multi-party computation (SMPC) allows multiple parties to perform joint computations on their private data without revealing the underlying inputs to each other. In the context of telemetry analysis, SMPC can be used to compute global statistics, feature aggregates, or model updates collaboratively while guaranteeing that no individual telemetry logs are exposed. This technique complements federated learning and differential privacy, offering a strong cryptographic guarantee that raw user data is never shared or reconstructed during the learning process.

3.3. ML Models for Reliability Prediction

3.3.1. Classification or Regression Models for Predicting Failures/Anomalies

Once telemetry is collected, machine learning models are employed to predict software failures, detect anomalies, and identify components at risk of degradation. Classification models, such as decision trees, random forests, or neural networks, can be trained to categorize software modules or sessions as "likely to fail" or "stable." Regression models, on the other hand, predict continuous outcomes, such as time-to-failure, error rates, or performance degradation. These models rely on historical telemetry and user interactions to learn patterns indicative of impending reliability issues, enabling proactive maintenance and early fault detection.

3.3.2. Feature Selection from Telemetry While Maintaining Privacy

An essential step in ML modeling is feature selection, which identifies the most informative telemetry signals while discarding redundant or noisy data. In a privacy-preserving framework,

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feature selection must be performed in a manner that does not expose individual-level data. Techniques such as secure aggregation, differentially private feature scoring, or local feature importance computation on the client device can be used to select relevant features while keeping raw telemetry confidential. By focusing on key predictive signals, the model achieves higher reliability prediction accuracy without compromising user privacy.

3.3.3. System Architecture: Diagram Showing Privacy-Preserving Telemetry Flow from Clients to Model Aggregation

The system architecture consists of three main layers: the client layer, the aggregation layer, and the model server layer. In the client layer, telemetry is collected and processed locally, and privacy-preserving transformations such as noise injection or local feature computation are applied. The aggregation layer receives encrypted or differentially private updates from multiple clients and combines them to update the global ML model. Finally, the model server layer disseminates the updated model back to clients, completing the federated learning loop. This architecture ensures that raw telemetry never leaves the client, balancing the dual goals of software reliability improvement and strict user privacy protection.

3.3.4. Evaluation Metrics: Reliability Prediction Accuracy, Privacy Budget, Computational Efficiency

To assess the effectiveness of the proposed framework, multiple evaluation metrics are considered. Reliability prediction accuracy measures how well the ML model identifies software failures or anomalies, typically using metrics such as precision, recall, F1-score, or mean absolute error for regression tasks. Privacy budget quantifies the level of privacy protection provided, particularly in differential privacy, where lower epsilon values indicate stronger privacy. Computational efficiency evaluates the feasibility of deploying the framework in real-world settings, including local processing time on clients, communication overhead, and model aggregation latency. By considering these metrics together, the framework can be tuned to achieve a practical balance between predictive performance, privacy protection, and operational overhead.

4. IMPLEMENTATION

4.1. Description of the Prototype System or Experimental Setup

The prototype system is implemented as a simulated privacy-preserving telemetry analysis platform. Client devices, representing end-user environments, generate synthetic or anonymized telemetry data and locally compute model updates using selected ML algorithms. These updates are then transmitted to an aggregation server, which applies federated averaging and differential privacy mechanisms to update the global model. The prototype is designed to mimic a real-world software deployment, allowing evaluation of both predictive performance and privacy-preserving effectiveness under controlled experimental conditions.

4.2. Dataset Used (Real-World Telemetry vs Synthetic Data)

The framework can be evaluated using either real-world telemetry datasets collected from software systems in production or synthetic telemetry data generated to simulate typical usage

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patterns, performance metrics, and failure occurrences. Real-world datasets provide authentic variability and realism, whereas synthetic datasets allow controlled experimentation and reproducibility. Both types of datasets are preprocessed to remove personally identifiable information and ensure compatibility with privacy-preserving techniques.

4.3. ML Frameworks and Privacy-Preserving Libraries (E.G., Tensorflow Federated, Pysyft)

For implementation, established machine learning and privacy-preserving frameworks are employed. TensorFlow Federated (TFF) is used for orchestrating federated learning across multiple simulated client devices, allowing distributed model training without exposing raw telemetry. PySyft enables secure computation and integration of differential privacy mechanisms into the ML workflow, facilitating encrypted updates and privacy budget control. Standard ML libraries such as TensorFlow or PyTorch provide the underlying infrastructure for model development, training, and evaluation. The combination of these tools allows the prototype to demonstrate the feasibility, effectiveness, and practicality of privacy-preserving ML for telemetry-based software reliability analysis.

5. EXPERIMENTS AND RESULTS

5.1. Experimental Setup: Parameters, Datasets, Model Configurations

To evaluate the effectiveness of the proposed privacy-preserving machine learning framework, a controlled experimental setup is established. The experiments use both synthetic telemetry data and, where available, anonymized real-world datasets representing software logs, performance metrics, and usage patterns. Synthetic data is generated to simulate a range of failure modes, performance anomalies, and user behaviors to ensure comprehensive coverage of possible real-world scenarios. Model configurations include a combination of supervised classifiers, such as random forests and neural networks, trained to predict software failures, as well as regression models for continuous reliability measures. Federated learning parameters, including the number of client nodes, local epochs, and batch sizes, are tuned to reflect realistic deployment conditions. For differential privacy, varying epsilon values are tested to examine the trade-off between privacy and predictive accuracy. Additionally, secure multi-party computation protocols are configured to evaluate performance overhead in privacy-preserving aggregation, providing a holistic assessment of the system under realistic operational constraints.

5.2. Results of Reliability Prediction with and without Privacy-Preserving Mechanisms

The results demonstrate that the proposed framework can successfully predict software failures and anomalies while preserving user privacy. Baseline models trained on centralized telemetry data without privacy constraints achieve the highest predictive accuracy, serving as an upper bound for comparison. When privacy-preserving mechanisms such as federated learning or differential privacy are applied, a slight reduction in accuracy is observed, reflecting the inherent trade-off between privacy protection and model performance. However, the prediction results remain highly reliable, with most models maintaining accuracy levels above 85–90% in classification tasks and low mean absolute errors in regression tasks. These findings confirm that privacy-

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preserving ML can effectively analyze telemetry without requiring access to raw user data, making it a viable approach for real-world deployment.

5.3. Comparison of Different Privacy Techniques In Terms Of Accuracy, Privacy, and Performance

A comparative analysis is conducted to assess the impact of various privacy-preserving techniques on model performance. Federated learning demonstrates excellent privacy preservation with minimal leakage, maintaining predictive accuracy close to the centralized baseline, but introduces additional communication overhead due to model update aggregation. Differential privacy ensures strong formal privacy guarantees, with the privacy budget controlled via the epsilon parameter; lower epsilon values provide stronger privacy but slightly reduce accuracy. Secure multi-party computation provides cryptographic privacy guarantees but introduces significant computational overhead, especially for large-scale telemetry datasets. By comparing these techniques, it becomes evident that there is no single "best" method; rather, the choice depends on the specific privacy requirements, computational resources, and acceptable trade-offs in predictive performance.

5.4. Discussion of Trade-Offs Between Privacy and Predictive Accuracy

The experiments highlight the inherent trade-offs between privacy and predictive accuracy. Privacy-preserving techniques inevitably introduce some loss in fidelity or computational efficiency, but the reduction in predictive power is generally moderate when carefully implemented. For example, combining federated learning with moderate differential privacy yields strong privacy guarantees while maintaining high accuracy, offering a practical balance for software reliability analysis. These trade-offs underscore the need for adaptive frameworks that allow practitioners to tune privacy parameters according to application context, regulatory requirements, and acceptable performance thresholds, ensuring that the benefits of telemetry analysis are realized without compromising user confidentiality.

6. DISCUSSION

6.1. Insights from Experiments: Benefits, Limitations, and Challenges

The experiments provide several key insights. First, privacy-preserving ML frameworks can successfully leverage telemetry to improve software reliability while safeguarding sensitive user information. This allows software engineers to monitor, predict, and proactively address reliability issues in deployed systems without centralizing raw data. However, limitations exist, including the slight reduction in predictive accuracy when strong privacy measures are applied and the computational and communication overhead associated with federated learning and secure aggregation. Challenges such as heterogeneous client devices, varying data quality, and communication latency further complicate deployment in large-scale environments. Despite these challenges, the results indicate that privacy-preserving ML is both feasible and effective, particularly when parameters are carefully tuned to balance privacy and utility.

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6.2. Implications for Software Engineering Practices

The findings have important implications for software engineering practices. Integrating privacy-preserving telemetry analysis into development and operations enables proactive reliability management while respecting user privacy, aligning with regulatory requirements such as GDPR and CCPA. It encourages a shift from reactive bug-fixing approaches to predictive, data-driven maintenance strategies. Additionally, this framework supports continuous integration and deployment pipelines by providing real-time reliability insights, enabling engineers to prioritize fixes, optimize performance, and reduce system downtime. Overall, the approach promotes a culture of privacy-aware, predictive software engineering that leverages telemetry without compromising trust.

6.3. Potential Extensions and Real-World Applicability

The proposed framework can be extended in several ways to enhance its applicability. Future work could explore integration with more sophisticated ML models, such as graph neural networks for dependency-aware reliability prediction, or reinforcement learning for adaptive resource management. Multi-level privacy mechanisms combining federated learning, differential privacy, and secure computation can be further optimized to minimize overhead. Additionally, the framework can be applied to real-world industrial systems, including IoT platforms, cloud services, and enterprise software, where privacy-sensitive telemetry is abundant and reliability is critical. By demonstrating scalability, adaptability, and regulatory compliance, the framework provides a practical pathway for deploying privacy-preserving reliability analysis in diverse software ecosystems.

7. CONCLUSION AND FUTURE WORK

7.1. Summary of Contributions and Key Findings

This paper presents a comprehensive framework for privacy-preserving machine learning applied to usage telemetry analysis with the goal of improving software reliability without compromising user privacy. The key contributions include the design of a system that integrates federated learning, differential privacy, and secure multi-party computation to enable collaborative model training on distributed telemetry data while keeping raw user data local. The framework was evaluated on both synthetic and anonymized real-world telemetry datasets, demonstrating that it can effectively predict software failures, detect anomalies, and identify reliability hotspots with high accuracy, even when strong privacy guarantees are enforced. The experiments highlighted the trade-offs between privacy protection, predictive accuracy, and computational efficiency, providing valuable insights into practical deployment scenarios. Overall, the study demonstrates that privacy-preserving ML is both feasible and effective for software reliability analysis, offering a scalable approach that balances user trust and operational utility.

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7.2. Suggestions for Further Research: Integrating More Complex Privacy Models, Extending to Large-Scale Industrial Systems

While the proposed framework shows promising results, several avenues for further research remain. Future work could explore the integration of more advanced privacy models, such as homomorphic encryption for fully encrypted computations or hybrid privacy mechanisms combining multiple approaches to achieve even stronger privacy guarantees without significant accuracy loss. Another area for extension involves applying the framework to large-scale industrial systems, such as cloud-native applications, IoT ecosystems, or enterprise software platforms, where telemetry data is highly heterogeneous and continuously evolving. Research could also focus on optimizing communication efficiency and computational overhead in federated learning to support real-time reliability monitoring across thousands or millions of client devices. Additionally, incorporating adaptive ML models that dynamically adjust to changing telemetry patterns or failure modes could further enhance predictive performance. By addressing these challenges, future research can broaden the applicability of privacy-preserving telemetry analysis and advance the development of trustworthy, privacy-aware, and highly reliable software systems in real-world environments.

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