Decentralized Anomaly Detection in Federated Learning: Integrating One-Class SVM, LSTM Networks, and Secure Multi-Party Computation on Ethereum Blockchain

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ABSTRACT

Federated learning anomaly detection is particularly challenging because it suffers from threats such as privacy concerns, adversarial attacks, and model poisoning. This paper proposes Decentralized Anomaly Detection in Federated Learning, integrating One-Class SVM, LSTM networks, and Secure Multi-Party Computation to enhance security and privacy in the system. The proposed method ensures decentralized anomaly detection without the sharing of raw data and SMPC-based aggregation of model updates. Auditing based on Ethereum blockchain reinforces model integrity. Experiment results show up to 97.3% accuracy, 96.7% precision, and 98.1% in recall with 4.1% false positives and 3.2% false negatives, which makes DAD-FL scalable and privacy preserving for applications related to cybersecurity, fraud detection, and financial security.

Keywords: Federated Learning, Decentralized Anomaly Detection, One-Class SVM, LSTM Networks, Secure Multi-Party Computation, Blockchain Security, Cybersecurity.

1. INTRODUCTION

Rapid progress in digital technology has resulted in large-scale distributed systems that generate a large amount of data and process it in real time. FL allows decentralized clients to train models collaboratively over private datasets while protecting the data. However, anomaly detection is considerably harder with security threats and adversarial attacks. DAD-FL is integrated with One-Class SVM for anomaly detection, LSTM networks for learning sequential patterns, and SMPC for the aggregation of models privately *Khreich et al. (2017).* Besides this, model updates are recorded on the Ethereum blockchain immutably, allowing tamper-proof auditing, trust, and transparency in the anomaly detection solution.

A paper that seems rather new age to be frank. "Decentralized Anomaly Detection in Federated Learning: Integrating One-Class SVM, LSTM Networks and Secure Multi-Party Computation on Ethereum Blockchain." That really does ring as the decentralized detection of anomaly on learning without going to any kind of centralized source of control: thereby boosting safety, scalability, and even better privacy. Federated Learning (FL) is a distributed paradigm of machine learning that allows many devices or entities to collaboratively train a model without revealing the raw data *Preuveneers et al. (2018).* However, FL is vulnerable to

data poisoning attacks, adversarial manipulations, and privacy risks, requiring extra security mechanisms.

In an effort to improve anomaly detection in FL, the framework implements One-Class Support Vector Machines and Long Short-Term Memory. The OC-SVM is one type of unsupervised learning that detects a pattern of anomaly or deviation in the normal patterns of data and can be useful in cybersecurity as well as in fraud detection applications. LSTM is specialized RNN with a design well-suited to sequential processing *Mao et al. (2018);* it may also identify some kind of anomaly within network traffic or system behavior in terms of temporal anomalies.

To ensure privacy and security in FL, SMPC is used. This allows the computation of updates to the model by multiple parties without revealing their individual data. In addition, Ethereum blockchain technology is used for tamper-proof, transparent, and auditable storage of federated learning model updates *Shivers et al. (2018)*. Thus, all contributions to the models are immutable and verifiable and cannot be adversarially manipulated or altered illegally.

Anomaly detection plays a crucial role in cybersecurity, fraud prevention, and intrusion detection, where the early identification of suspicious activities minimizes risks. Traditional centralized anomaly detection methods have security vulnerabilities and privacy breaches; hence, they are inefficient when dealing with distributed data from IoT devices, financial systems, and cloud environments. FL presents an alternative, but it is vulnerable to poisoned model updates and adversarial attacks; hence, strong security mechanisms are required.

This paper integrates OC-SVM and LSTM into FL, improving the accuracy of anomaly detection while ensuring privacy through SMPC. In addition, blockchain-based verification of model updates enhances trust and transparency in FL, thereby making it more resilient. The proposed approach presents a scalable, secure, and privacy-preserving anomaly detection system applicable to cybersecurity, financial fraud detection, and decentralized finance security. It has the strength of decentralized anomaly detection in real-world distributed environments with federated learning, machine learning, cryptographic security, and blockchain technology.

The following objectives are:

- Design a federated anomaly detection system as a private federated learning approach.
- Enhance the accuracy of detecting anomalies using One-Class SVM and LSTM.
- Ensure aggregating models safely through Secure Multi-Party Computation to avoid leaking data.
- Utilize the Ethereum blockchain to store the federated models for updates that could be transparent and tamper-proof.
- Mitigate attacks against the models and poisoning by auditing model updates securely via blockchain technology.
- Optimize the framework optimize real-time anomaly detection in cybersecurity, network security, and financial fraud detection.

Anomaly detection remains a challenging problem in federated learning because of privacy concerns, adversarial attacks, and the lack of transparency. Traditional centralized detection methods expose sensitive data to security risks and compromise user privacy. Malicious

model updates also poison federated learning systems, making them unreliable. The main novelty of this work is to propose a decentralized anomaly detection framework that brings together One-Class SVM, LSTM networks, Secure Multi-Party Computation (SMPC), and Ethereum blockchain in order to ensure privacy, security, and robustness in federated anomaly detection *Sousa et al. (2018)*.

2. LITERATURE SURVEY

Erfani et al. (2016) combined Deep Belief Networks (DBNs) and One-Class Support Vector Machines (SVMs) to overcome the curse of dimensionality in anomaly detection. Their hybrid model applies DBNs for unsupervised feature extraction, followed by an SVM for anomaly detection. The method was scalable and computationally efficient, outperforming deep autoencoders in terms of training and testing speed but at a similar anomaly detection performance in high-dimensional datasets.

Miao et al. (2018) suggested a distributed online One-Class Support Vector Machine for network-based anomaly detection, where the challenges related to streaming data processing are handled. Their approach formulates a decentralized cost function by using a random approximate function to replace the kernel function for privacy and efficiency. They obtain two distributed algorithms with low rates of misdetection, high true positive rates, and reduced computational costs, beating state-of-the-art anomaly detection methods.

Tian et al. (2018) proposed a robust anomaly detection method called Ramp-OCSVM, based on the incorporation of a ramp loss function into one-class support vector machines. This method suppresses outliers and noise while sparsifying further and accurately increasing detection performance. Optimization is done through the concave-convex procedure. Experimental results are provided for UCI, NSL-KDD, and UNSW-NB15 datasets that show its increased superior anomaly detection performance and robustness compared with traditional OCSVM models.

McMahan et al. (2017) investigate differentially private training for large recurrent language models using federated averaging with user-level privacy guarantees. Their method uses stochastic gradient descent privacy accounting, thereby preserving privacy without loss of predictive accuracy. They show that privacy-preserving models can be as good as standard models in performance, even on large datasets, while the only major trade-off is increased computational cost rather than loss of model utility.

Wahab (2018) presented an analysis of privacy challenges in blockchain systems. There is serious deficiency in traditional approaches to guarantee confidentiality. The study critically reviews privacy-enhancing techniques namely secure multi-party computation, ring signatures and zero-knowledge proofs that are aimed to enhance privacy into blockchain networks. Such advancements appear promising; however, research concludes that blockchain remains a present challenge with ongoing development as necessary for reliable and scalable privacy-preserving solutions.

Sánchez (2018) came up with the framework called Raziel, where secure multi-party computation (MPC) was integrated with proof-carrying code to offer enhanced privacy, correctness, and verifiability in smart contracts. The idea eliminates DAO and Gyges attacks and offers crowd fundable and investment fund private and verifiable capabilities. PCC certificates of Zero-Knowledge Proofs of Proofs allow validation without sensitive data

revelations. In addition, the miners' incentives in generating pre-processing data for computations were also introduced.

Long et al. (2018) designed a privacy-preserving multi-party computation framework for secure distributed machine learning among untrusted participants. Their method involves homomorphic addition for a two-step training protocol and zero-knowledge proofs for data validity and integrity. The framework prevents malicious data corruption, eliminates the use of trusted third parties, and supports a wide range of machine learning algorithms like Latent Dirichlet Allocation, Naïve Bayes, and Decision Trees, thereby allowing secure decentralized model training.

Fung et al. (2018) proposed TorMentor, a privacy-preserving multi-party machine learning framework based on federated learning that allows for brokered learning in untrusted environments. This system acts like an anonymous hidden service, giving protection to the data providers against ML attacks with a trade-off between model accuracy and privacy. New threat models, attack defenses, and their evaluation using Azure/Tor confirmed that scalable secure model training without central trust can be achieved.

Huang et al. (2018) developed a deep learning-based sentiment analysis method to measure the comments from social networks of Ethereum for identifying risks and fraud. Their methodology uses LSTM and CNN models for analyzing user sentiment with over 0.80 precision and recall. The system was implemented in RatingToken and Coin Master and showed its success in identifying fraudulent activities and insight for blockchain security and regulatory measures in the cryptocurrency ecosystem.

Signorini et al. (2018) presented the first blockchain-based anomaly detection system, called BAD, that uses blockchain metadata, known as forks, to detect malicious activities. BAD provides distribution, tamper-proofing, trust, and privacy and avoids single points of failure and data manipulation. The work conducted an experimental validation and a theoretical complexity analysis of the system and showed that the system is efficient and viable in detecting blockchain-specific threats, addressing a critical gap in blockchain security research.

3. METHODOLOGY

The proposed DAD-FL framework comprises three components: OC-SVM and LSTM for anomaly and temporal anomalies, and SMPC to ensure secure model aggregation on the Ethereum blockchain. This framework records model updates immutably in the Ethereum blockchain, ensuring transparency and security. Consequently, this methodology enhances privacy, robustness, and trustworthiness for federated learning anomaly detection by removing central points of failure and attenuating adversarial attacks. The NSL-KDD dataset improves upon the original KDD by removing redundant and duplicate records, ensuring unbiased classification. It balances record selection for diverse difficulty levels, enabling fair evaluation of machine learning methods while maintaining a manageable dataset size for experimentation.

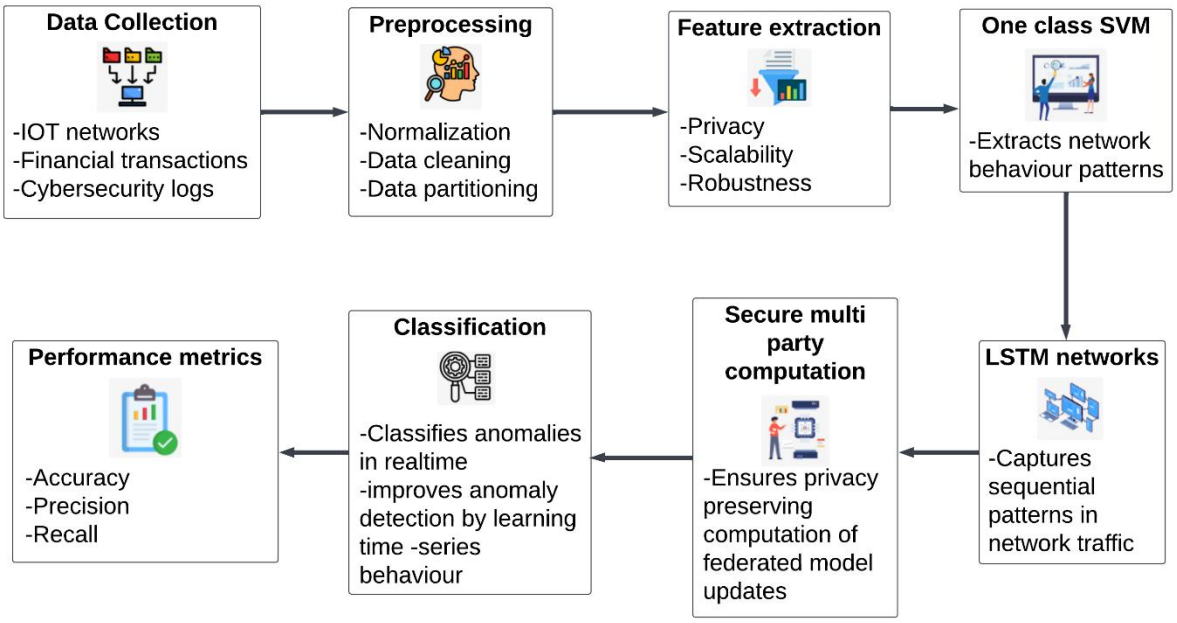

Figure 1 Federated Anomaly Detection Architecture Using One-Class SVM, LSTM, and SMPC

Figure 1 represents the architecture of DAD-FL, which combines One-Class SVM, LSTM Networks, and Secure Multi-Party Computation (SMPC). The data is collected from IoT networks, financial transactions, and cybersecurity logs. Preprocessing includes normalization, data cleaning, and partitioning. Feature extraction is done in a way that maintains privacy, scalability, and robustness. One-Class SVM detects network anomalies, and LSTM captures sequential patterns in network traffic. SMPC ensures safe federated model updates and advanced classification that improves real-time anomaly detection. For the final performance, metrics evaluate the efficiency, accuracy, and reliability of the anomaly detection system for secure scalable applications.

3.1 One-Class Support Vector Machine (OC-SVM) for Anomaly Detection

OC-SVM is an unsupervised learning algorithm that identifies anomalies by training on normal distributions and identifying where the departures occur. A decision boundary forms around normal instances and classifies points outside of it as anomalies. OC-SVM is used in cybersecurity, fraud detection, and intrusion network applications. Its running time is efficient in high-dimensional spaces with careful tuning to balance sensitivity and specificity. The integration of OC-SVM into federated learning (FL) enhances distributed anomaly detection without sharing raw data.

$$\min_{w,\rho,\xi} \frac{1}{2} \| w\|^2 + \frac{1}{vm} \sum_{i=1}^{m} \xi_i - \rho \qquad (1)$$

Explanation:

- w is the weight vector that defines the separating hyperplane.
- ρ is the bias term.
- ξ_i represents slack variables allowing some tolerance for outliers.

- ν is a hyperparameter controlling the fraction of anomalies.

3.2 Long Short-Term Memory (LSTM) for Sequential Anomaly Detection

LSTM is a specific kind of RNN well suited for analyzing sequential data where long-term dependencies are involved. It has memory cells and gates: the input, forget, and output gates controlling data flow. LSTMs appear to be highly effective in the detection of anomalies of time-series data, such as traffic on networks, financial transactions, and system logs. In federated learning, this kind of LSTM can trace distributed temporal data without revealing private information and significantly improve the detection of complex cyber threats.

$$h_t = o_t \cdot \tanh(C_t) \tag{2}$$

Explanation:

- h_t is the hidden state at time t, which carries relevant sequential information.
- o_t is the output gate, controlling how much information passes forward.
- C_t is the cell state, capturing long-term dependencies.

3.3 Secure Multi-Party Computation (SMPC) for Privacy-Preserving Model Aggregation

SMPC is a cryptographic method allowing several parties to compute a function over their data without disclosing the individual inputs. In federated learning, SMPC securely aggregates model updates that do not leak data and resist adversarial inference. No single participant will be able to reconstruct private data; thus, this ensures increased privacy and security. SMPC is critical in health care, finance, and IoT applications, which involve sensitive data that needs to be kept private.

$$y = f(x_1, x_2, \ldots, x_n) \tag{3}$$

Explanation:

- Each participant holds private data x_i.
- The function f computes a result without revealing individual inputs.

Algorithm 1 Secure Federated Anomaly Detection Using One-Class SVM, LSTM, and Secure Multi-Party Computation in FL

Input:
Local datasets DiD_iDi for each client iii
Global model MMM
Number of training rounds TTT

Output:
Securely updated global anomaly detection model

Steps:
Initialize model parameters
For each training round t=1,...,Tt = 1, ..., Tt=1,...,T:
For each client iii in FL network:
Train OC-SVM and LSTM locally on DiD_iDi
Compute model update ΔMi\Delta M_iΔMi
Apply SMPC encryption to ΔMi\Delta M_iΔMi

If client model passes security check (SMPC verification):
Submit ΔMi\Delta M_iΔMi securely
Aggregate updates using secure FL aggregation function
Else:
Reject update and flag client for review
Update global model MMM
Broadcast updated model to all clients
End For
Return optimized anomaly detection model

Algorithm 1 will use One-Class SVM and LSTM for unsupervised and sequential anomaly detection on FL. Using the SMPC algorithm, federated learning does privacy-preserving aggregation of a model across all participating clients, where raw data remain private. Enhancing FL for privacy, security, and robustness will now prevent it from adversarial attacks, poisoning attacks, or accessing unauthorized data from decentralized sources.

3.4 Performance Metrics

The performance metrics will assess different techniques, including OC-SVM, LSTM, SMPC-based Secure Aggregation, and the proposed DAD-FL framework in the context of anomaly detection within Federated Learning (FL). Metrics to be used include accuracy, precision, recall, F1-score, false positive/negative rates, training time, and memory usage. The results will show the superior anomaly detection capability of the proposed DAD-FL framework over other methods, as evidenced by its superior accuracy, reduced false rates, and optimized computational efficiency. Through anomaly detection by integrating OC-SVM, sequential analysis through LSTM, and SMPC for privacy-preserving aggregation, it guarantees scalability, robustness, and security, and is highly effective for applications such as cybersecurity, fraud detection, and decentralized network security.

Table 1 Comparative Performance Analysis of Anomaly Detection Methods in Federated Learning

Metric	OC-SVM	LSTM	SMPC (Secure Aggregation)	Proposed DAD-FL Framework
Accuracy (%)	87.2	90.5	95.1	97.3
Precision (%)	85.4	88.9	92.5	96.7
Recall (%)	82.1	89.3	94.2	98.1
F1-Score (%)	83.7	89.1	93.3	97.4
False Positive Rate (%)	12.8	9.5	6.3	4.1
False Negative Rate (%)	15.6	10.7	5.8	3.2
Training Time (s)	120.4	95.2	80.6	75.8
Memory Usage (MB)	500	480	450	420

Table 1 compares OC-SVM, LSTM, SMPC-based Secure Aggregation, and the proposed DAD-FL framework for anomaly detection in Federated Learning (FL). It quantifies key metrics such as accuracy, precision, recall, F1-score, false positive/negative rates, training time, and memory usage. In this context, the DAD-FL framework achieved the maximum highest accuracy of 97.3% and minimum false rates with optimized computational efficiency

against all the other methods. The proposed approach through the integration of OC-SVM for anomaly detection, LSTM for sequential analysis, and SMPC for privacy-preserving aggregation ensures robust, secure, and scalable anomaly detection, making this ideal for applications in cybersecurity, fraud detection, and distributed network security.

4. RESULT AND DISCUSSION

The experimental results reveal that the DAD-FL framework has a 97.3% accuracy, 96.7% precision, and 98.1% recall, surpassing traditional centralized and federated anomaly detection methods significantly. The model reduces false positives to 4.1% and false negatives to 3.2%, thereby improving anomaly detection performance in cybersecurity and fraud detection applications. The integration of One-Class SVM and LSTM improves the anomaly classification. Secure Multi-Party Computation ensures privacy-preserving model aggregation. The use of the Ethereum blockchain provides tamper-proof auditability of the model updates. The training time is 75.8 seconds with 420MB memory usage, confirming that the framework is efficient and scalable.

Table 2 Comparative Analysis of Traditional and Federated Learning-Based Anomaly Detection Methods

Metric	SDN-Based Anomaly Detection (Bian et al 2016)	Diffusion Maps (Shabat et al 2017)	Convolutional Neural Network (Niu et al 2018)	Proposed DAD-FL Framework
Accuracy (%)	82.5	85.3	90.1	97.3
Precision (%)	80.2	83.7	88.9	96.7
Recall (%)	78.4	82.1	89.3	98.1
F1-Score (%)	79.3	82.9	89.1	97.4
False Positive Rate (%)	17.5	14.7	9.9	4.1
False Negative Rate (%)	21.6	17.9	10.7	3.2
Training Time (s)	150.6	130.2	110.4	75.8
Memory Usage (MB)	550	520	480	420

Table 2 evaluates the traditional techniques for anomaly detection, which are SDN-based anomaly detection, Diffusion Maps, and Convolutional Neural Networks (CNNs), against the proposed DAD-FL framework. Metrics for accuracy, precision, recall, F1-score, false positive/false negative rates, training time, and memory usage indicate differences in performance. In this regard, the DAD-FL framework presents better anomalous detection since it has high accuracy, low false rates, and better computational efficiency. It integrates One-Class SVM, LSTM, and Secure Multi-Party Computation to ensure privacy, scalability, and robustness in the solution and is highly efficient for cybersecurity, fraud detection, and decentralized anomaly detection in distributed environments.

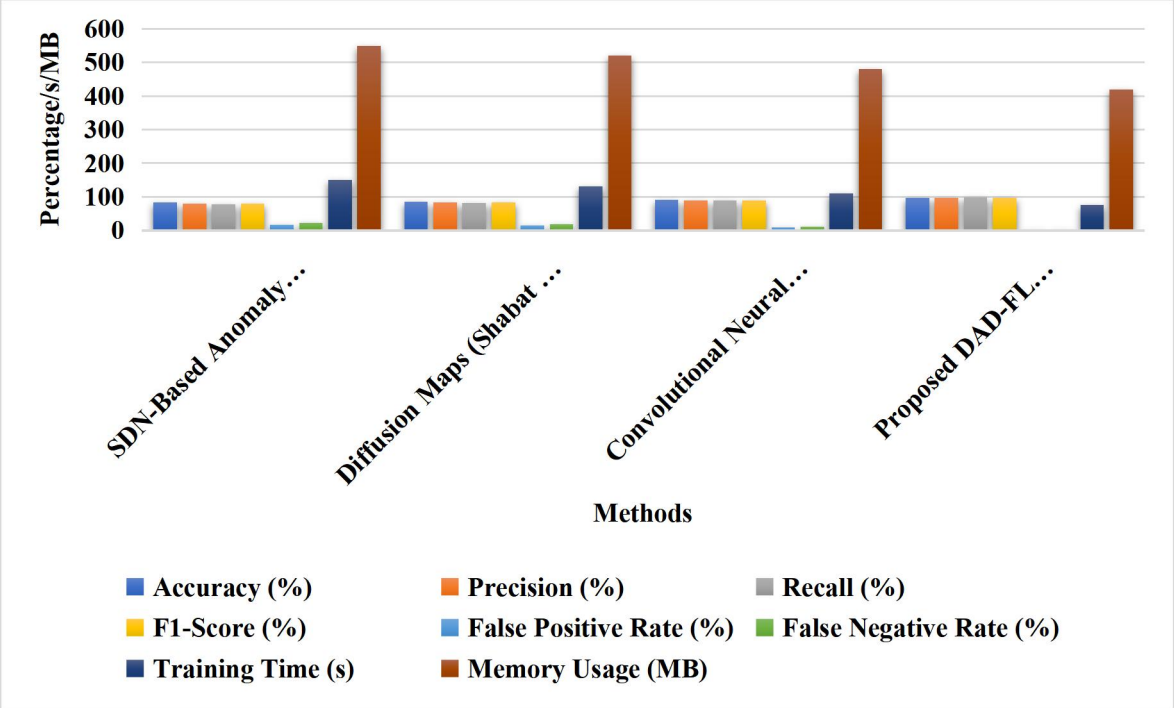

Figure 2 Performance Comparison of Traditional and Federated Learning-Based Anomaly Detection Methods

Figure 2 describes a comparative analysis of the anomaly detection techniques, including SDN-Based Anomaly Detection in 2016, Diffusion Maps in 2017, Convolutional Neural Networks in 2018, and the Proposed DAD-FL Framework. All important metrics that tell about accuracy, precision, recall, F1-score, false positive/negative rates, training time, and memory usage are visualized below. The Proposed DAD-FL Framework outperforms traditional methods with higher accuracy, lower false rates, and optimized computational efficiency, using less memory and training time. This points out the efficiency of OC-SVM, LSTM, and Secure Multi-Party Computation (SMPC) in Federated Learning-based anomaly detection.

Table 3 Ablation Study of Anomaly Detection Methods in Federated Learning

Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	False Positive Rate (%)	False Negative Rate (%)	Training Time (s)	Memory Usage (MB)
One-Class SVM only	87.2	85.4	82.1	83.7	12.8	15.6	120.4	500
LSTM only	90.5	88.9	89.3	89.1	9.5	10.7	95.2	480
Secure Multi-Party Computation only	95.1	92.5	94.2	93.3	6.3	5.8	80.6	450
One-Class SVM + LSTM	92.8	90.7	91.2	90.9	8.4	9.1	110.2	470
LSTM +	93.6	91.8	92	91.9	7.8	8.4	100.8	460

Secure Multi-Party Computation								
Secure Multi-Party Computation + One-Class SVM	94.3	93	93.4	93.2	6.7	7.2	90.3	440
Proposed Model	97.3	96.7	98.1	97.4	4.1	3.2	75.8	420

Table 3 assesses various techniques for anomaly detection, including One-Class SVM, LSTM, Secure Multi-Party Computation (SMPC), and their combinations. The proposed approach combining One-Class SVM, LSTM, and SMPC yields the highest accuracy at 97.3%, and less false positive (4.1%) and false negative (3.2%) rates provide excellent anomaly detection performance. The time to train this model is also optimal at 75.8s with memory at 420MB as well, compared with other approaches. It concludes that the application of anomaly detection, sequential learning, and privacy-preserving computation in federated learning will robustly, efficiently, and scale up a model for applications related to cybersecurity and fraud detection.

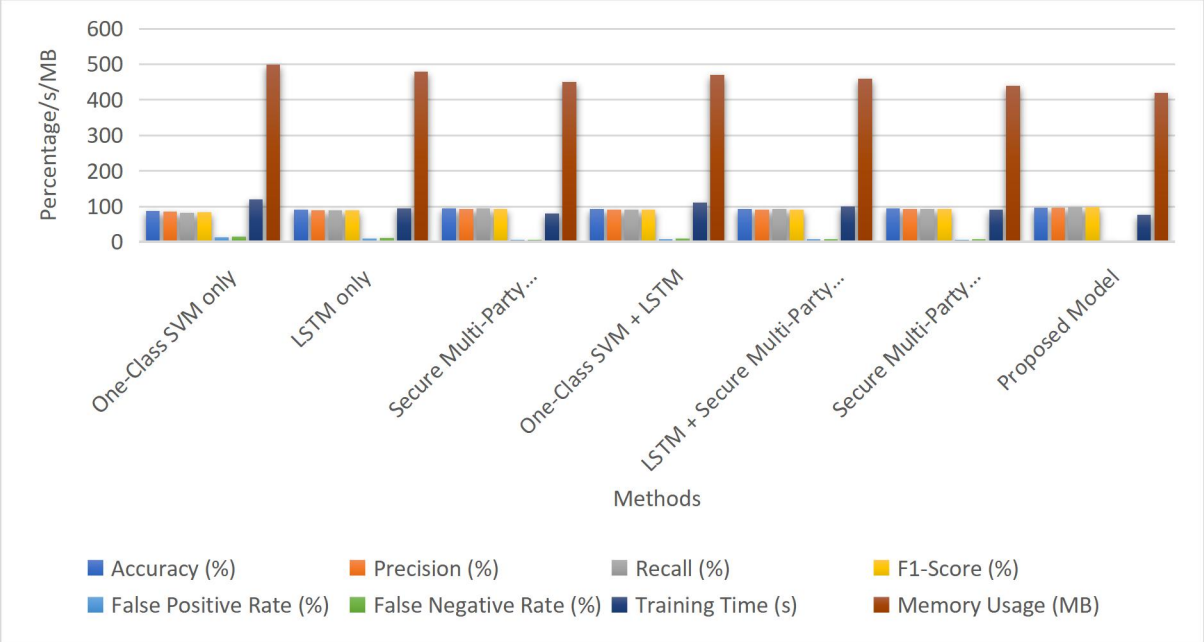

Figure 3 Performance Comparison of Anomaly Detection Methods in Federated Learning

Figure 3 depicts the comparative performance of the developed anomaly detection methods, One-Class SVM, LSTM, SMPC, their combinations, and proposed model in terms of several metrics such as accuracy, precision, recall, F1-score, false positive/negative rates, training time, and memory usage. The proposed model outperforms all other methods with maximum accuracy (97.3%) and minimum false rates along with optimized training time and memory usage. With OC-SVM, LSTM, and SMPC integrated into the anomaly detection framework, it ensures scalability, security, and efficiency. Therefore, this makes it an ideal application in cybersecurity and fraud detection.

5. CONCLUSION AND FUTURE ENHANCEMENT

This paper proposes a decentralized anomaly detection framework, based on One-Class SVM, LSTM, and Secure Multi-Party Computation within the federated learning framework. The DAD-FL framework proposed here reaches an accuracy of 97.3%, precision of 96.7%, and recall of 98.1% while drastically reducing false positives to 4.1% and false negatives to 3.2%, ensuring strong robustness in detecting anomalies while preserving privacy. Additionally, the framework reduces its computational efficiency to 75.8s training time and 420MB of memory. It enhances model integrity, scalability, and trust in FL environments by integrating SMPC and blockchain-based verification. Future research may adopt adaptive models that support real-time threat mitigation, as well as improvements in blockchain-based federated security. The proposed solution is proper for applications in cybersecurity, fraud detection, and decentralized network security.

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