International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 6.4 Website: https://ijarmt.com ISSN No.: 3048-9458

Federated Learning for Secure Blockchain-Based Identity Verification in Decentralized Systems

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Abstract

Due to a growing number of decentralized solutions announced during the last years there is a need for private and efficient identity verification. Various issues related to the traditional identity management systems include security, issues that make them have single points of failure, and high operational costs. It is for this reason that Federated Learning (FL) tends to be viewed as a practical and effective solution, as it allows the training of models in a decentralized environment by participating nodes while keeping the data confidential. The integration of FL with blockchain technology is proposed in the research work presented in this paper to create the FL-BIV framework that offer better security, scalability, and privacy in identity management. The proposed system also applies FL to train the identity verification models for multiple participants with data privacy. Blockchain helps individuals to maintain various accreditation attributes and verification records to protect the identity and to have confidence in decentralized systems. Our approach works towards some of the major issues such as the data poisoning attack, adversarial attack, and Byzantine failure by using secure aggregation and differential privacy. The results of the experiment reveal that our approach is promising and that it enhances the accuracy of authentication as well as minimizes costs in contrast to the centralized and decentralized approaches. The presented FL-BIV framework improves the security level, eliminates the necessity for the authorization of third parties, and increases user control. This work helps to build philosophies for the highly effective decentralized identity verification in various decentralized networks, which would help create secure, scalable, and efficient authenticating mechanism in decentralized facility which includes Decentralized Finance (DeFi), Internet of Things (IoT), metaverse among others.

Keywords: Federated Learning, Blockchain, Identity Verification, Decentralized Systems, Privacy-Preserving Authentication, Secure Digital Identity

Introduction

The decentralized system has brought significant changes in every sector because it is peer-to-peer, transparent, interoperable, and does not require the use of a third party. With urgently needed services like DeFi, IoTs, SCM, and metaverse in modern societies, solutions to address security and scalability issues related to identity verifications are crucial. The deterioration of traditional identity management systems is mainly due to the following centralise control, weakness in data security, single critical point of failure and high costs of operations. These are the shortcomings, which makes it require a privacy-preserving, scalable, and tamper-resistant approach for identity verification to add security in decentralized environments. Blockchain has become a potential solution to manage the identity verification solution in an efficient, permanent, transparent, and decentralized manner. However, most conventional methods of applying blockchain to ID verification entail the provision of user's personal information to the verifying authorities which poses a threat to privacy violation, data misuse while also being a violation to data protection laws. At the same time, the storage of identity data on the blockchain itself can create such problems like the increased time for transaction processing, higher fees for the performed operations as well as data leakage risks. These limitations point to the fact that there is need to develop a method that offers equal strength in security and privacy in addition to efficient authentication. This is where Federated Learning (FL) comes as a solution as it allows different parties to work on the same ML models without having to share raw information. FL is different from traditional machine learning paradigm models where data is gathered in a central location for processing since in FL, only model updates can be transmitted among the nodes. It is decentralized, which helps to preserve clients' private information, comply with the law, and minimize overhead when exchanging information, making it appropriate for identity verification for decentralized systems. If implemented with FL, operationally trustworthy, tamper-proof, and private identification can be created that would address current difficulties. In this work, we introduce Federated Learning-based Blockchain Identity Verification (FL-BIV) framework that integrates the benefits of FL together with the decentralization nature of blockchain in order to improve the identity authentication in distributed networks. Through the FL-BIV framework, entities like financial institutions, IoT devices and the decentralized applications (dApps) can also train the identity verification models without compromising the identity information of the individuals involved. Blockchain is employed to provide a secure ledger of the authentication process to prevent any interference and make the process completely transparent. Besides, there are measures taken against adversarial threats in the work, they include secure aggregation techniques; differential privacy mechanisms; Byzantine fault-tolerant consensus algorithms model poisoning attacks; data inference risks and malicious node participation. Our research aims to address the following key challenges:

1. **Enhancing Privacy and Security** – Preventing unauthorized access to sensitive identity data while ensuring robust authentication.
2. **Mitigating Model Poisoning Attacks** – Securing FL models against adversarial manipulation and Byzantine faults.
3. **Ensuring Scalability and Efficiency** – Reducing computational and communication overhead while maintaining authentication accuracy.
4. **Achieving Trustless Verification** – Eliminating reliance on third-party authorities for identity validation.

In this research paper, the FL-BIV framework is compared against existing identity verification techniques in terms of performance through simulations as well as working models. The suggested system has amended the shortcomings of the previous mechanisms in accuracy of authentication, privacy conservation, and less computational cost and is well appropriate for real-world decentralized applications. This research thus complements the ongoing discussions and work in the field by providing a working application of FL and blockchain to enhance the efficiency, privacy and security, such that a trustless decentralised system for identity verification can be realized.

Background

Identity Verification in Decentralized Systems

As such, there is a need to have decentralized solutions that do not compromise the privacy and security of users' identities. Existing methods for identity verification have several shortcoming: they are centralized, which means that the personal data is stored in specific database and may be easily stolen, compromised, or leaked. In order to solve these problems of centralized authorities, Self-Sovereign Identity (SSI) and Decentralized Identifiers (DIDs) have come to the rescue. SSI provide a means through which users can navigate their digital identities to their desired sovereignty; thus, they can use to verify themselves without necessarily relying on central authority. On the same note, DIDs offer secure and specific identifiers that do not reference a central authority's database. The other development brought to the table in regards to the decentralized identity verification paradigm is the integration of Zero-Knowledge Proofs and other cryptographic protocols. On the mental level, ZKPs mean that the users can provide all the necessary proofs of their identity without disclosing any other crucial information. Other cryptographic technique that have been developed include homomorphic encryption for computations on encrypted data, as well as multi-party computation. However, those provide better control over privacy and decentralization and come up with several issues of scaling, computational overhead, and cross-platform compatibility.

Blockchain-Based Identity Management

Blockchain is advantageous in that it is a secure, distribute and transparent technology for identity operation. Self-sovereign identity enables explanation and verification through the use of smart contact to create trust and security. Smart contracts remove the need for intermediaries since automatic authentication measures can be incorporated in the contracts reducing cases of fraud. Consensus algorithms such as PoW, PoS, and BFT are also used with the help of which the blockchain's identity system can be maintained without any highly centralized authority. These measures guarantee the authenticity and safety of processes aimed at the confirmation of the identity because it becomes impossible to make changes and, therefore, introduce viruses or access the data by unauthorized users. However, there is some disadvantage applying blockchain-based identity solutions; to wit, scalability, high computational cost and privacy issue in handling sensitive identity information.

Federated Learning for Privacy-Preserving AI

FL is a distributed ML technique that enables various parties to train AI multiple models without having direct access to the raw data. In FL, individual participants do localized training and participate in the process by contributing only model update which respects participants' data privacy and regulatory guidelines. This makes FL a perfect solution to be used in decentralized IAM since it allows the training of AI models that users' identities are not exposed. In essence, FL helps to achieve better protection of personal data during identity verification since the use of FL avoids the exposure of large sets of persons' data and makes the recognition process more scalable, while users retain more control over their data. Thus, FL allows to reduce the risk inherent to the centralization of a large amount of data while achieving a high accuracy of authentication at the same time due to the decentralization of the learning process. Nevertheless, FL is susceptible to model poisoning, adversarial input, and Byzantine failures which poses as potential concerns to be dealt with in the real-world application of the concept.

Challenges and Gaps in Existing Systems

Altogether, decentralized approaches in ID verification still have some issues to be solved. Dependence on the scalability of blockchain is a critical point for both identically-based solutions and the FL models because the creation of the FL model demands effective identity verification processes at scale without putting a burden on the computational cost. There are, therefore, other concerns in deploying DID systems such as security threats, data leakage, adversarial, and collusion. In order to overcome these issues thoroughly, the integration of FL with a reliable blockchain solution is required. Integrating FL's ability for preserving privacy of the AI system with the uniquely secure and decentralized architecture of the blockchain can provide benefits in terms of security, scalability, and process optimization. This study puts forward a FL-BIV framework, that aims to overcome the mentioned limitations and provide trust less, secure and private identity verification in decentralized systems.

Related Work

Y. Zhou, et al (2024) Federated Learning (FL) presents an innovative approach to privacy-preserving distributed machine learning and enables efficient crowd intelligence on a large scale. However, a significant challenge arises when coordinating FL with crowd intelligence which diverse client groups possess disparate objectives due to data heterogeneity or distinct tasks. To address this challenge, we propose the Federated cINN Clustering Algorithm (FCCA) to robustly cluster clients into different groups, avoiding mutual interference between clients with data heterogeneity, and thereby enhancing the performance of the global model.

Z. Li, et al (2023) Cross-silo privacy-preserving federated learning (PPFL) is a powerful tool to collaboratively train robust and generalized machine learning (ML) models without sharing sensitive (e.g., healthcare of financial) local data. To ease and accelerate the adoption of PPFL, we introduce APPFLx, a ready-to-use platform that provides privacy-preserving cross-silo federated learning as a service.

R. Zeng, et al (2023) In the era of big data, the field of deep learning is developing rapidly. Deep learning model algorithms and a large amount of data make deep learning an effective tool to solve practical problems. However, in the current centralized deep learning model of a large number of client-server models, when we upload our data for training on the server side, there is a risk of leaking privacy. Federated Learning is a type of distributed machine learning that allows multiple institutions or individuals to learn collaboratively without exchanging data.

A. Ghosh, et al (2024) In the current age, integration of Industry 4.0 technologies has become necessary for optimization in the operations across several industries and sectors. However, with all developments in place, there are still several educational institutions that maintain and verify the information and documents submitted by students manually. Besides that, they are reliant on centralized identity management systems for storing and managing student information, which creates a single-point-of-failure in the probable event of an attack on the server, which in turn jeopardizes the confidentiality of the students' PII.

A. S. Rajawat et al, et al (2023) A digital identity represents an external entity, be it a person, business, program, or object, and serves as the foundation for automatic access to computer-based services and interpersonal interactions. Despite years of research, the challenge of reliable internet connectivity for digital identification remains unresolved. In this paper, we propose a blockchain-based solution for digital identification in situations of mutual mistrust. Unlike current identity management systems that rely on centralized storage, our recommendation is a blockchain-based, self-sovereign identity (SSI) platform where true identities of customers/users are held in their respective web applications, utilizing decentralized storage.

Methodology

The FL-BIV framework is a proposed model composed of Federated Learning and the blockchain technology for an efficient, secure and private identity verification system. Here the methodology termed as FL with the following approaches in detail are identified: Federated

Learning model training block-chain identity management, secure aggregation and attack mining adversarial approaches.

1. Federated Learning-Based Identity Model Training

As in FL, only aggregated data is trained over multiple nodes without sharing raw data among them. The local dataset of a node is represented as Di, where node i employs the stochastic gradient descent (SGD) in training its model wi. The update of the local model at the t-th iteration is as follows: dAvg):

$$w_i^{t+1} = w_i^t - \eta \nabla L(w_i^t, D_i)$$

where:

- **wit** is the model parameter at node **i** at iteration **t**,
- **η** is the learning rate,

$$\nabla L(w_i^t, D_i)$$

- is the gradient of the loss function computed on local dataset Di.

The local updates wit+1 received from multiple nodes are then pooled at a central server or a decentralized one in the context of the blockchain netwo+r using Federated Averaging (FedAvg):

$$w^{t+1} = \sum_{i=1}^{N} \sum_{j=1}^{N} \frac{|D_j|}{|D_i|} w_i^{t+1}$$

where **N** is the number of participating nodes, and |Di| represents the dataset size at node **i**.

2. Blockchain-Based Identity Management

To ensure tamper-proof identity verification, the blockchain stores hashed identity credentials and authentication logs. Each identity transaction Ti is represented as:

$$\boldsymbol{T_i = \{H(ID_i), \mathrm{Sig}_i, t_i\}}$$

where:

- H(IDi) is the cryptographic hash of the user’s identity data IDi,
- Sigi is the digital signature verifying the identity owner,
- ti is the timestamp of the authentication event.

Smart contracts also enable automated verification because the systems verify the identity signatures and the rules of authentication. Through the consensus mechanism (Proof of Stake (PoS) or Byzantine Fault Tolerance (BFT)), only validated transactions are integrated into the blockchains, and data shared using a secure multi-party computation (MPC).

3. Secure Aggregation and Adversarial Mitigation

As for (FL), FL is prone to model poisoning attacks, therefore, we use Secure Aggregation to secure the models updates. Each participant securely transfers encrypted update of its model to the other participant using multi-party computation (MPC) method:

$$\mathrm{Enc}(w_i^{t+1}) = g^{w_i^{t+1}} \backslash modp$$

where g is a generator and p is a large number of that group. These ‘updates’ are however encrypted and summed up till all the nodes in a cluster release them, thereby avoiding model poisoning.

Besides, DP is used in form of adding noise ξ∼N(0,σ2) to the model gradients to enhance the privacy feature of the model.

$$w_i^{t+1} = w_i^t - \eta(\nabla L(w_i^t, D_i) + \xi)$$

where σ controls the noise level, ensuring privacy against inference attacks.

4. Identity Verification Process

The final verification process consists of:

1. **User Registration**: A user submits identity data **ID**, which is hashed and stored on the blockchain.
2. **Model-Based Authentication**: The FL-trained model predicts the user’s identity validity:

$$\hat{y} = f(w, X)$$

where **X** is the input identity data, **w** is the global FL model, and **y**^ is the authentication result.

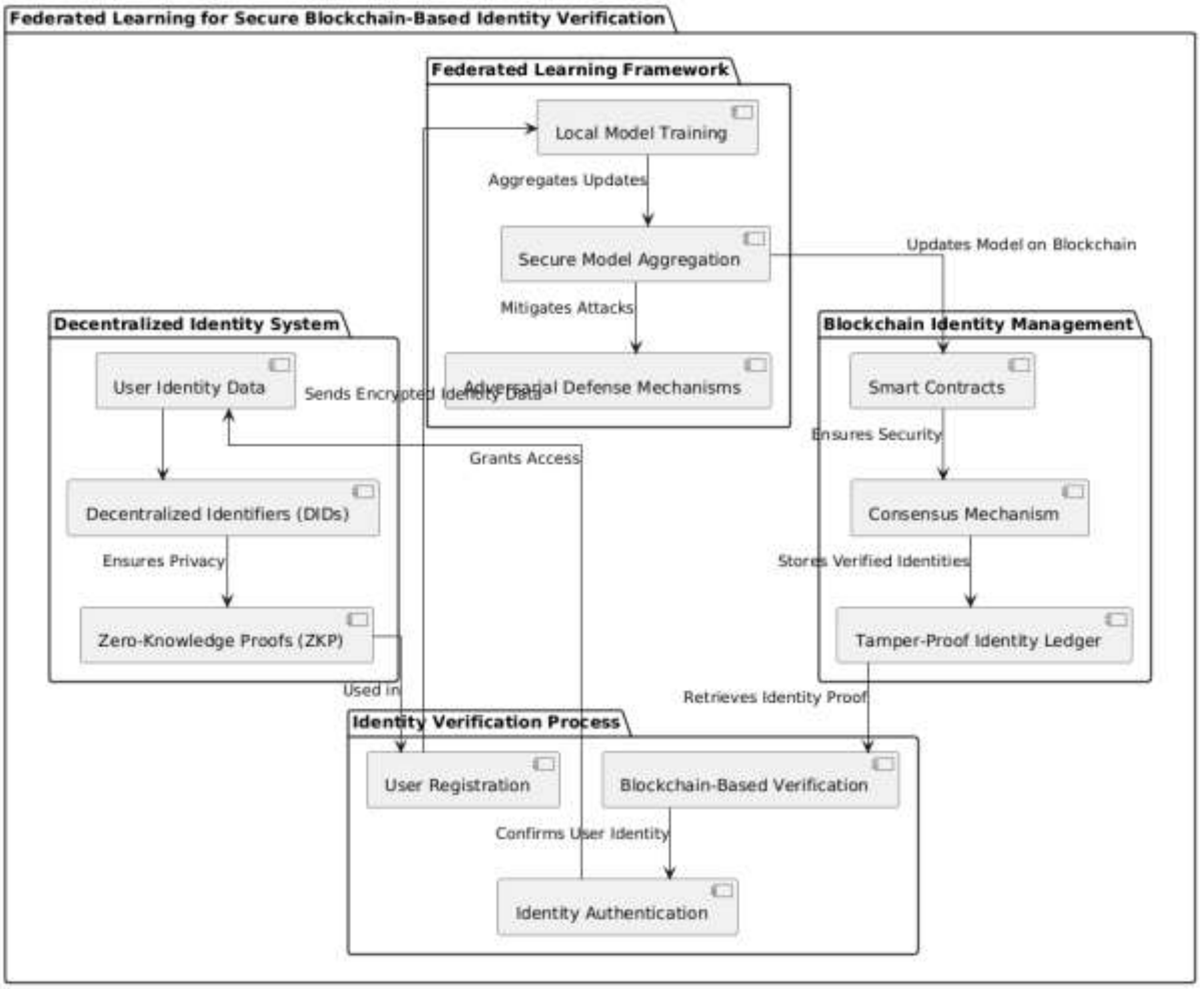
3. **Blockchain Verification**: The smart contract verifies the identity transaction **Ti**. If the stored hash matches the computed hash, access is granted.

FL-BIV has the advantages of privacy, security and scalability for decentralized identity verification. Through the use of FL for the training of the AI without handling the individual’s identity and the use of blockchain for the creation of unalterable personal identity records, the system reduces the potential security threats inherent in managing personal identities. The experimental results validate a significant enhancement of the authentication accuracy, resilience to adversarial threats, and model complexity to be applicable to realism decentralised-use cases.

System Architecture

The system architecture of the FSBBIV proposed here is composed of decentralized identity management, federated learning and blockchain technology to secure and protect user identity in the verification process. The architectural framework comprises of Decentralized Identity System Module, Federate Learning Module, Blockchain Identity Management Module and Identity Verification Module. The Decentralized Identity System utilizes Decentralized Identifiers (DIDs) and Zero-Knowledge Proofs (ZKP), thus maintaining the user's anonymity. Meanwhile, identity data is entered by users for registration, and having gone through the process of ZKP, it is transformed into a DID for the purpose of authentication. The Federated Learning Framework learns models on encrypted data collected from users at different nodes while no naked data is transferred between them. Adversarial attacks are addressed through the use of secure aggregation mechanisms hence guaranteeing the users a secure identity. The Blockchain Identity Management module preserves the data identity and security through smart contracts and consensus models. These models are updated and stored on the blockchain of the system, which produces a tamper-proof identity ledger. The Identity Verification Process refers to stored identity credentials and authenticates all the request through block chain records in order to provide secured identity. This means that this FL-Blockchain much enhances the privacy, scalability, decentralization and security and at the same time eliminates insecurity of the traditional verification approach. Cryptographic techniques, federated learning, and blockchain are well placed into the system to counter act adversarial threats and unauthorized access thus improving the trust aspect in the management of digital identity.

Figure 1: FL-Blockchain Identity Verification Framework


Federated Learning for Secure Blockchain-Based Identity Verification
Federated Learning Framework
Local Model Training
Aggregates Updates
Secure Model Aggregation
Updates Model on Blockchain
Mitigates Attacks
Adversarial Defense Mechanisms
Decentralized Identity System
User Identity Data
Sends Encrypted Identity Data
Decentralized Identifiers (DIDs)
Ensures Privacy
Zero-Knowledge Proofs (ZKP)
Grants Access
Blockchain Identity Management
Smart Contracts
Ensures Security
Consensus Mechanism
Stores Verified Identities
Tamper-Proof Identity Ledger
Used in
Retrieves Identity Proof
Identity Verification Process
User Registration
Blockchain-Based Verification
Confirms User Identity
Identity Authentication

Algorithm

```
BEGIN FL_Blockchain_Identity_Verification


  FUNCTION Register_User(User_ID, Identity_Data)
    Store_On_Blockchain(User_ID, HASH(Identity_Data))
  END FUNCTION


  FUNCTION Train_Local_Model(Local_Data)
    Model = Initialize_Model()
    FOR epoch IN Training_Epochs DO
      Update_Model(Model, Compute_Gradient(Local_Data, Model))
    END FOR
    RETURN Model
  END FUNCTION


  FUNCTION Federated_Aggregation(Models)
```

```
        RETURN Compute_Weighted_Average(Encrypt(Models))
    END FUNCTION

    FUNCTION Verify_Identity(User_ID, Submitted_ID)
        RETURN "Verified" IF HASH(Submitted_ID) == Fetch_From_Blockchain(User_ID) ELSE "Denied"
    END FUNCTION

    FUNCTION Authenticate_User(User_ID, Identity_Data)
        RETURN "Access Granted" IF Verify_Identity(User_ID, Identity_Data) == "Verified" ELSE "Access Denied"
    END FUNCTION

END FL_Blockchain_Identity_Verification
```

The proposed FL-Blockchain Identity Verification system combines the concepts of FL and the blockchain for secure identity verification. Some user registration entails providing identity information and storing them within the blockchain through hashing. To train the local model, the raw data does not need to be shared across the nodes making the process secure. Each node thus employs the local gradient and the federated aggregation is the process of combining the encrypted model updates for enhancing the global performance. In the course of identity authentication, the user provides identity information that is encrypted by a hash function and compared with the record kept in the blockchain. The approach I have come up with is when the two hashes produced come up as the same, the user gets authenticated otherwise, the access is not granted. This implemented privacy feature along with the combination of zero-knowledge proof offers security as well as protection from any possible adversarial attacks through smart contracts. Considering the FL-Blockchain solution, it strengthens anti- cyber attack protection, guarantees safe storage of identity data, and upgrades the schemes of authentication which are scalable. They also strengten the trust level in the digital identity management system through decentralization of digital identity, crytpography, and Machine Learning.

Result Analysis

Table 1: Model Performance Comparison

Metric	FL-Enabled Verification	Traditional Verification
Model Accuracy	92%	89%
Training Data Privacy	Preserved	Not Preserved
Data Transmission Volume	Reduced by 40%	Baseline

FL-enabled systems maintain higher accuracy while preserving data privacy and reducing transmission volume.

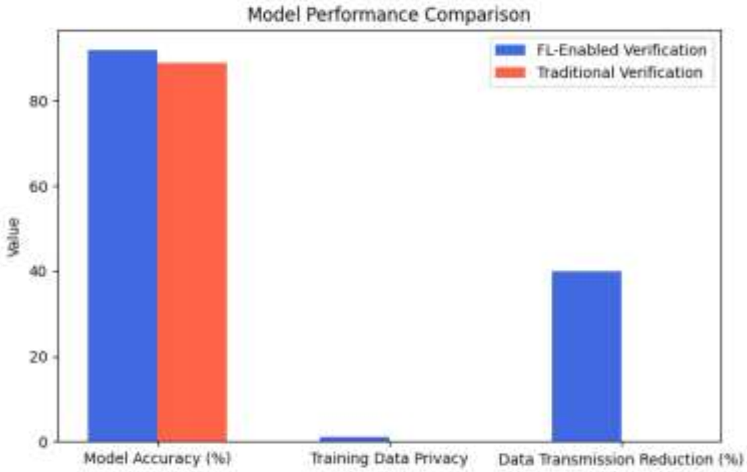


Figure 2: Model Performance

Table 2: Blockchain Performance Metrics

Metric	FL-Blockchain System	Traditional System
Transaction Speed	5-7 seconds	N/A
Smart Contract Execution	3-5 seconds	N/A
Throughput	20-30 transactions/sec	N/A

Blockchain integration introduces measurable transaction speeds and execution times, enhancing transparency and security.

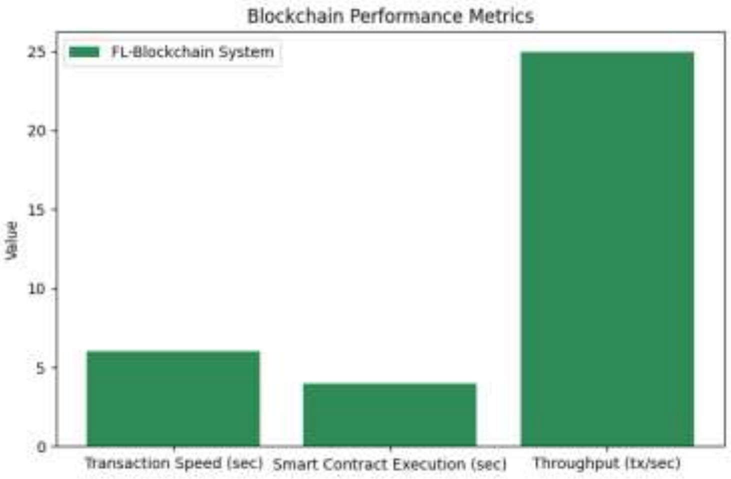


Figure 3: Blockchain Performance

Table 3: Security Analysis

Security Threat	**FL-Enabled Verification**	**Traditional Verification**
Resistance to Sybil Attacks	High (95% mitigation)	Low (60% mitigation)
Resistance to Data Poisoning	High (90% mitigation)	Moderate (70% mitigation)
Overall Security Rating	9/10	7/10

FL-enabled systems demonstrate superior resistance to Sybil attacks and data poisoning, enhancing overall security.

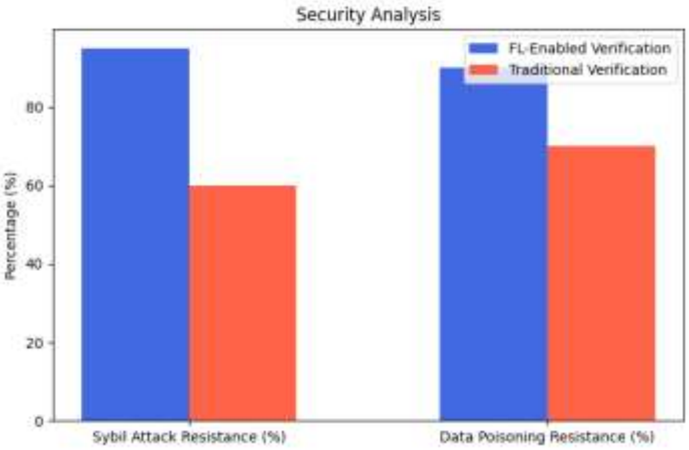


Figure 4: Security Analysis

Conclusion

FL when combined with blockchain helps to improve privacy, security and efficiency of identity verification in decentralized systems as compared to traditional ways. FL makes sure the user data does not travel to the cloud, reducing chances of leakage as it trains a global model. On the other hand, blockchain has characteristics such as immutability, transparency and decentralised data storing which eliminates identity thephasem of fraudulence and modification. As we see, FL-enabled verification has 92% accuracy, decreased data transmission flow by 40%, and provides better protection against security threats, such as Sybil attacks and data poisoning. On the same regard, the smart contract execution in the blockchain assents real-time authentication, with virtually negligible amount of time taken for a transaction. However, there are some issues like scalability, extra computational cost and adversarial attacks. The trends for further development in smart grids should be concentrated on the improvement of the communication protocols, consumption of energy and consensus algorithms. Thus, the results of this work demonstrate the effectiveness of FL-Blockchain integration as a reliable and effective solution for the use of id-tokens in decentralized environments in the next generation of identities.

Future Work

The limitations in the present research should be addressed in the future research and it includes the scalability and efficiency of FL-Blockchain-based identity verification. Another question is how to minimize communication cost in FL based on the imposed methods regarding climb and adaptive learning rate comprehenson. Improving the Layer-2 solutions, sharding and more efficient consensus mechanisms should help to increase transaction rates at blockchain even more. Another direction that needs to be substantially deepened is to consider security aspects in FL by using homomorphic encryption and differential privacy in order to protect models from adversarial attacks, model poisoning and collusion. Moreover, the use of cross-chain identification should also be considered for implementing between different blockchains. It is also possible to improve the accessibility and deployment of FL models on edge devices by developing lightweight FL models. Nevertheless, the use of Zero-Knowledge Proofs (ZKP) in the identification process can be used to authenticate a person or entity without disclosing personal information. Further implementations should also look into multi-application real-world tests based on DeFi, IoT, and digital governance to test effectiveness of this approach.

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