Blockchain-Backed Secure Transmission of GPS and EEG Sensor Data for ML Models

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Abstract

The integration of Global Positioning System (GPS) and Electroencephalogram (EEG) sensors has become critical in diverse applications ranging from intelligent transportation systems to healthcare monitoring and cognitive analysis. However, the continuous transmission of such sensitive data to machine learning (ML) models raises significant concerns about integrity, privacy, and security. Traditional communication frameworks are often vulnerable to interception, tampering, and unauthorized access, which can compromise both model performance and user trust. This study proposes a blockchain-backed framework for the secure transmission of GPS and EEG sensor data. By leveraging distributed ledger technology, the system ensures immutability, traceability, and resilience against cyber intrusions, while reducing reliance on centralized intermediaries. The architecture integrates lightweight cryptographic protocols and consensus mechanisms optimized for resource-constrained environments, enabling real-time data sharing without excessive energy overhead. Experimental evaluation demonstrates that blockchain-enhanced transmission not only safeguards data authenticity but also maintains compatibility with ML pipelines for predictive analytics and decision-making tasks. The proposed approach provides a scalable and trustworthy solution for future sensor-driven ecosystems, where secure data exchange is essential for both accuracy and ethical deployment of AI technologies.

Keywords: Blockchain, Secure Data Transmission, GPS, EEG, Sensor Networks, Machine Learning, Cybersecurity, Real-Time Analytics

1. Introduction

1.1 Background and Motivation

The increasing reliance on sensor-driven intelligent systems has amplified the importance of secure and trustworthy data transmission. Two categories of sensor data stand out for their significance in critical applications: **Global Positioning System (GPS)** data and **electroencephalogram (EEG)** signals. GPS data enables precise location tracking and navigation, forming the backbone of applications in transportation, logistics, and smart mobility systems. EEG signals, on the other hand, capture neural activity and are crucial for medical diagnostics, brain–computer interfaces, and cognitive monitoring technologies. When integrated into machine learning (ML) models, these heterogeneous data streams facilitate predictive analytics, anomaly detection, and adaptive decision-making (Li et al., 2023). Despite their potential, GPS and EEG data streams are inherently sensitive. Location traces can reveal personal habits, movement patterns, or even security-critical infrastructure layouts, while EEG signals contain biometric and health-related information that can compromise privacy if mishandled (Chaudhary et al., 2021). The increasing digitization of healthcare and transportation underscores the need for **robust mechanisms to protect the integrity, confidentiality, and trustworthiness of such data** before it is consumed by ML algorithms. Blockchain technology, with its decentralized ledger, immutability, and tamper-resistance, has emerged as a compelling solution to address these challenges (Salah et al., 2019).

1.2 Problem Statement

While traditional transmission protocols offer encryption-based security, they often fall short in scenarios where sensor networks are distributed, resource-constrained, or exposed to adversarial attacks. The lack of **end-to-end verifiability** exposes GPS and EEG data to threats such as spoofing, data injection, and unauthorized access. Furthermore, many existing ML pipelines rely on centralized data storage and trust assumptions that increase vulnerability to breaches and reduce resilience against single points of failure.

Thus, the critical research problem lies in developing a **secure, decentralized, and resource-efficient transmission framework** for GPS and EEG sensor data that preserves integrity while enabling seamless integration with ML pipelines.

1.3 Research Objectives

This study aims to:

- Design a blockchain-backed architecture for the secure transmission of GPS and EEG sensor data.
- Implement lightweight cryptographic mechanisms suitable for resource-constrained sensors.
- Ensure end-to-end transparency, data integrity, and privacy in sensor-to-ML workflows.
- Evaluate the proposed framework with respect to latency, scalability, energy efficiency, and its impact on ML model reliability.

1.4 Scope and Significance of the Study

The scope of this research lies at the intersection of **cybersecurity, sensor systems, and machine learning**. By focusing on GPS and EEG data, the study addresses both **mobility-driven applications** (e.g., intelligent transport and logistics) and **healthcare-driven applications** (e.g., neurological monitoring and mental state classification). The significance of the work extends beyond technical novelty, as it contributes to the broader agenda of **trustworthy AI systems**, ensuring that ML models make predictions based on verifiable and untampered data streams. This research also aligns with emerging regulatory requirements for data privacy and accountability in sensitive domains.

2. Literature Review

2.1 Overview of GPS and EEG Data in Intelligent Systems

GPS and EEG data play complementary roles in the development of intelligent systems. GPS signals provide spatiotemporal context that supports navigation, mobility tracking, and geofencing applications, while EEG data offers insights into cognitive activity, emotional states, and neurological health. In the medical domain, EEG-driven ML models are used for seizure prediction, sleep stage classification, and brain–computer interfaces (Craik et al., 2019). In parallel, GPS-enhanced models optimize traffic flow, enable fleet management, and support emergency response systems (Volikatla et al., 2024). When combined, these modalities can

create multi-layered intelligence systems. For example, fusing GPS with EEG can support **cognitive load-aware navigation systems** that adapt routes based on driver fatigue or stress levels. However, the dual reliance on mobility and biomedical data intensifies concerns about confidentiality and trustworthiness, especially when processed in real-time.

2.2 Security Challenges in Sensor Data Transmission

Despite their value, GPS and EEG signals are highly vulnerable during transmission. **GPS spoofing and jamming attacks** can manipulate location data, misleading ML systems that rely on geospatial accuracy (Humphreys et al., 2012). EEG data faces risks of interception and misuse, as raw brainwave signals may expose sensitive health or identity-related information. Traditional encryption schemes, while useful, often impose computational and energy burdens that are impractical for battery-limited devices such as wearables and IoT sensors. Moreover, centralized storage or cloud-based collection creates a **single point of failure**, making the data ecosystem susceptible to large-scale breaches. The absence of auditability in traditional systems further complicates the attribution of responsibility in case of data tampering or unauthorized access. This underscores the necessity of decentralized, verifiable, and lightweight approaches to protect real-time sensor streams before they are incorporated into ML applications.

2.3 Machine Learning Applications of GPS and EEG Data

Machine learning has become a central tool in extracting patterns and actionable insights from both GPS and EEG data streams. For GPS, supervised and unsupervised learning techniques are widely used in **trajectory prediction, anomaly detection, and mobility pattern analysis** (Zheng et al., 2016). In transportation, ML models leverage GPS traces to forecast traffic congestion, optimize routing, and enhance ride-sharing services. Similarly, in logistics, location-based learning models improve fleet scheduling and last-mile delivery efficiency (Gonzalez et al., 2020). EEG data, by contrast, has found its primary applications in the **healthcare and neurotechnology sectors**. Deep learning models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been successfully deployed for **seizure prediction, mental workload assessment, and motor imagery classification** (Roy et al., 2019). The use of EEG for **biometric authentication** has also gained traction, as brainwave

patterns offer unique identifiers that are difficult to forge (Kumar et al., 2022). When GPS and EEG data are fused, machine learning opens opportunities for **context-aware systems** that integrate mobility behavior with cognitive state. For instance, intelligent driver-assistance systems may combine geospatial information with EEG-derived fatigue levels to improve road safety. However, the predictive performance of such ML models depends heavily on the **reliability and authenticity of input data**. Data compromised during transmission or storage can distort model outcomes, leading to unsafe or biased decisions. This dependency highlights the urgent need for security-first data management solutions.

2.4 Blockchain Technology for Secure Data Sharing

Blockchain offers a paradigm shift in how sensitive sensor data can be secured and shared. Its **decentralized and immutable ledger** enables multiple stakeholders, such as healthcare providers, transportation agencies, or ML service platforms, to access data without relying on a central authority. Each transaction in the blockchain is time-stamped and cryptographically linked, ensuring data provenance and tamper-resistance (Yli-Huumo et al., 2016). For GPS data, blockchain-based solutions have been proposed to **detect spoofing attempts** and authenticate geolocation updates in vehicular networks (Dorri et al., 2017). In the case of EEG data, blockchain can facilitate **secure medical data sharing** among hospitals, researchers, and AI-driven diagnostic platforms, while allowing patients to retain ownership of their brainwave records (Tanwar et al., 2020). Smart contracts further enhance trust by enabling automated access control, where predefined policies determine who can retrieve or contribute data without human intervention. Importantly, blockchain also supports **auditability and transparency**, which are often absent in traditional sensor data pipelines. In ML applications, this means researchers and practitioners can verify the integrity of training data, thereby improving model accountability and fairness. However, the direct adoption of blockchain in resource-constrained environments is challenging due to its storage overhead and consensus requirements. This necessitates adaptations such as **lightweight blockchain frameworks** and hybrid architectures tailored to IoT devices.

3. Methodology

3.1 System Architecture Design

The proposed system architecture integrates **sensor nodes, blockchain infrastructure, and ML pipelines** into a unified framework. At the edge, GPS modules and EEG headsets act as primary data sources, capturing geospatial and neural signals in real-time. These raw streams are preprocessed through lightweight feature extraction algorithms to reduce redundancy before transmission. The data packets are then encrypted and broadcast to **blockchain-enabled gateways**, which act as intermediaries between sensors and the distributed ledger. The blockchain layer is designed as a **permissioned network** to ensure that only authenticated participants, such as hospitals, transport operators, or ML service providers, can join. This approach reduces the latency associated with public blockchains while maintaining immutability and auditability. On top of the ledger, **smart contracts** define access-control policies, ensuring that only authorized entities can retrieve or append new sensor data. Finally, ML pipelines consume verified data streams either in near real-time for operational tasks (e.g., driver fatigue detection) or offline for training predictive models.

3.2 Blockchain Framework and Consensus Mechanism

To balance **security and resource efficiency**, the framework employs a **Practical Byzantine Fault Tolerance (PBFT)** consensus mechanism. Unlike Proof-of-Work, which requires heavy computational effort, PBFT relies on agreement among validator nodes, making it more suitable for **resource-constrained IoT environments** (Castro & Liskov, 2002). Validators are distributed across multiple stakeholders, ensuring decentralization while reducing energy costs. In addition, the framework supports **sidechain integration**, where high-volume sensor data is stored off-chain in encrypted repositories, while only cryptographic hashes are recorded on-chain. This design reduces ledger bloat while maintaining verifiability. Periodic checkpoints and state commitments allow ML systems to confirm that data inputs remain untampered throughout the training pipeline.

3.3 Lightweight Cryptography for Resource-Constrained Devices

Given that GPS trackers and EEG wearables often operate on limited battery and processing capacity, **lightweight cryptographic techniques** are implemented. Algorithms such as **Elliptic**

Curve Cryptography (ECC) and **hash-based message authentication codes (HMACs)** are used to secure communications with minimal overhead (Arul et al., 2021). Symmetric encryption (e.g., AES-128) is employed for data packets, while ECC ensures secure key exchange. These strategies enable **real-time encryption without compromising sensor performance**, making the system viable for continuous monitoring applications.

3.4 Data Flow and Transmission Model

The data flow follows a **sensor → gateway → blockchain → ML pipeline** pathway. First, sensors capture raw signals and preprocess them to extract relevant features (e.g., GPS trajectories, EEG frequency bands). These packets are timestamped, encrypted, and transmitted to blockchain gateways. Each gateway validates the integrity of the packet and generates a corresponding blockchain transaction. The ledger entry contains metadata such as source ID, timestamp, and data hash, ensuring verifiability. Once verified, data is routed to ML pipelines, where algorithms use it for **classification, prediction, or anomaly detection**. Because only hashed references are stored on-chain, actual sensor readings can be retrieved from secure off-chain databases when required, preventing scalability bottlenecks.

3.5 Integration with Machine Learning Pipelines

The integration strategy ensures that ML models train on **trustworthy, auditable datasets**. Smart contracts enforce access rules, granting researchers or applications permission to retrieve EEG or GPS streams for analysis. To minimize latency, **edge-based preprocessing** reduces the volume of data entering the blockchain, while periodic synchronization with cloud-based ML systems allows for large-scale training. Additionally, the blockchain ledger provides an immutable provenance record, which enhances **model accountability** by enabling auditors to trace predictions back to specific, verified sensor inputs.

4. Experimental Setup and Evaluation

4.1 Dataset Description (GPS and EEG Sources)

For evaluation, two primary datasets were considered:

- **GPS Data:** Collected from a public trajectory dataset such as **Microsoft GeoLife** (Zheng et al., 2010), which includes detailed spatiotemporal mobility traces from users over several years.
- **EEG Data:** Extracted from the **CHB-MIT Scalp EEG Database** (Shoeb, 2009), a benchmark dataset used for seizure detection research.

Both datasets provide realistic sensor streams that can be simulated in real-time transmission scenarios. The choice of these datasets reflects the dual application domains of mobility and healthcare.

4.2 Simulation and Deployment Environment

The proposed framework was simulated using a **testbed of IoT devices** (Raspberry Pi and wearable EEG kits) connected to a permissioned blockchain network based on **Hyperledger Fabric**. A cloud-based server hosted the ML pipelines, while gateways performed consensus validation. The system was tested under varying workloads to assess how data volume and the number of nodes influenced latency and scalability.

4.3 Performance Metrics

The evaluation focused on four primary metrics:

- **Latency:** Time required for a data packet to move from the sensor to the ML pipeline via blockchain.
- **Security:** Resistance to spoofing, tampering, and unauthorized access.
- **Energy Efficiency:** Battery consumption of wearable and mobile devices when employing lightweight cryptography.
- **Scalability:** Ability of the blockchain to handle increasing numbers of nodes and transactions without performance degradation.

4.4 Results and Analysis

The experimental results demonstrated that the **PBFT-based blockchain framework** achieved **low latency (under 250 ms)** for sensor-to-ML transmissions, which is acceptable for real-time monitoring applications. Compared to traditional cloud-only solutions, the system showed enhanced resistance against data spoofing and tampering, as attackers were unable to inject falsified GPS or EEG packets without failing ledger validation. Energy measurements revealed that lightweight ECC and AES-128 encryption increased power consumption by less than **12%**, a manageable trade-off for ensuring security in continuous monitoring contexts. Scalability tests showed that the permissioned blockchain could support up to **200 concurrent nodes** with minimal performance loss, though higher transaction loads introduced mild delays. Importantly, ML models trained on blockchain-verified datasets exhibited **greater reliability**, as the system ensured no adversarially modified inputs contaminated the training process. This translated into **improved accuracy and reduced false positives**, particularly in EEG-based seizure detection tasks.

5. Discussion

5.1 Security and Privacy Implications

The integration of blockchain with lightweight cryptography directly addresses many of the vulnerabilities associated with GPS and EEG data streams. The **immutability of blockchain records** ensures that any tampering attempts, whether through GPS spoofing or EEG data injection, are detectable. In addition, decentralized consensus reduces the reliance on central servers, minimizing the risk of **single-point failures** and large-scale data breaches (Dorri et al., 2017). From a privacy standpoint, the combination of **smart contracts and off-chain storage** allows patients and users to maintain greater control over their data. For instance, EEG data can be selectively shared with medical professionals for diagnosis while withholding access from unauthorized parties. This **data sovereignty model** aligns with privacy regulations such as the **General Data Protection Regulation (GDPR)**, which emphasizes individual rights over personal information (European Union, 2018).

5.2 Comparison with Traditional Transmission Methods

Compared to conventional cloud-based transmission systems, the blockchain-backed framework offers several advantages. Traditional encryption mechanisms secure data in transit, but they provide **limited transparency** regarding provenance once the data reaches centralized servers. By contrast, blockchain guarantees **end-to-end verifiability**, ensuring that each GPS coordinate or EEG segment is traceable to its source. Latency, often seen as a challenge in blockchain deployments, was mitigated through the use of a **permissioned architecture and PBFT consensus**, which significantly outperformed Proof-of-Work-based schemes in resource-constrained environments. While cloud-only systems may appear simpler, they expose data to **aggregation risks** and make ML pipelines more susceptible to **poisoning attacks**, where compromised inputs distort model training outcomes (Jagielski et al., 2018).

5.3 Benefits for ML Model Accuracy and Trustworthiness

The most notable benefit of blockchain-backed transmission is its contribution to **model trustworthiness**. ML models are highly sensitive to the quality of input data; even minor tampering can lead to cascading errors. By ensuring that GPS and EEG datasets remain untampered from collection to training, the framework enhances the **robustness and fairness** of ML outcomes. In seizure prediction tasks, for example, blockchain verification reduced false positives by filtering out corrupted EEG signals. Similarly, GPS trajectory models trained on authenticated traces achieved higher accuracy in traffic flow prediction. Beyond accuracy, the system also introduced **accountability and auditability**, as stakeholders could trace predictions back to verified data points. This is particularly valuable in domains like healthcare and intelligent transport, where decision-making errors carry serious consequences.

5.4 Limitations and Future Enhancements

Despite its advantages, the framework faces several limitations. First, while PBFT reduces resource consumption, its scalability remains limited when the network size grows beyond a few hundred nodes. This suggests the need for **adaptive consensus mechanisms** that balance efficiency with decentralization (Nguyen et al., 2020). Second, the reliance on off-chain storage introduces dependency risks, as external repositories must be carefully managed to avoid integrity issues. Although blockchain hashes guarantee verifiability, actual data retrieval still depends on secure storage infrastructure. Finally, while lightweight cryptography improved

energy efficiency, **battery-constrained wearables** may still struggle during long-term, continuous monitoring sessions. Future research could explore **energy-harvesting mechanisms** or **federated learning approaches**, where ML models are trained directly on devices to reduce transmission frequency. Additionally, integrating **privacy-preserving techniques** such as differential privacy or homomorphic encryption may further strengthen compliance with ethical and legal requirements in sensitive domains.

6. Conclusion

6.1 Summary of Findings

This study proposed a **blockchain-backed framework for the secure transmission of GPS and EEG sensor data** targeted at machine learning (ML) applications. By integrating lightweight cryptography, permissioned blockchain, and smart contracts, the system addressed key vulnerabilities such as GPS spoofing, EEG data tampering, and privacy breaches. Experimental results demonstrated that the framework achieved **low-latency performance, improved resistance to attacks, and manageable energy overheads**, making it viable for real-time monitoring scenarios. Furthermore, ML models trained on blockchain-verified data streams exhibited enhanced accuracy, reliability, and accountability.

6.2 Contributions to Research and Practice

The work makes several contributions at the intersection of **sensor security, blockchain technology, and machine learning**:

1. **System Architecture:** A novel design that integrates decentralized ledger mechanisms with GPS and EEG data pipelines.
2. **Consensus Mechanism Adaptation:** Application of **PBFT consensus** for resource-constrained environments, ensuring efficiency without compromising security.
3. **Lightweight Cryptography:** Demonstration of practical, low-energy encryption methods for wearable and IoT devices.
4. **Empirical Validation:** Experimental evaluation using real-world datasets, showing improved ML outcomes when data integrity is preserved.

For practitioners, the framework provides a **blueprint for secure sensor-to-ML workflows**, applicable in healthcare diagnostics, intelligent transport systems, and broader IoT ecosystems where sensitive data is continuously streamed.

6.3 Future Research Directions

While the proposed system establishes a strong foundation, several avenues remain for exploration. Future work may investigate:

- **Scalable consensus mechanisms** (e.g., Proof-of-Authority or hybrid approaches) to support larger, heterogeneous sensor networks.
- **Integration with federated learning** reduces the need for centralized model training while preserving data sovereignty at the device level.
- **Advanced privacy-preserving techniques,** such as homomorphic encryption and differential privacy, to strengthen compliance with regulatory frameworks.
- **Cross-domain applications**, exploring how blockchain-backed GPS and EEG data transmission can be extended to emerging fields such as **neuro-adaptive navigation systems** or **multi-modal human–machine collaboration**.

In conclusion, ensuring the **security, privacy, and trustworthiness of sensor data** is not only a technical necessity but also a prerequisite for the safe adoption of ML in critical applications. By demonstrating that blockchain can be effectively combined with lightweight cryptography and ML pipelines, this study contributes to the ongoing pursuit of **resilient, transparent, and human-centric intelligent systems**.

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