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Securing IoHT Data Using AI and Ethereum Blockchain for Anomaly Detection

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ABSTRACT:

The evolution of the Internet of Healthcare Things (IoHT) has improved patient engagement and care, but it has also increased the risks associated with cybersecurity. This project proposes a novel framework that integrates Artificial Intelligence (AI) with the Ethereum blockchain and IPFS to provide anomaly detection and secure health data. Effective threat detection requires the application of multiple machine learning models, such as SVM, Random Forest, and CNN1D, to the TON_IoT dataset. Decentralized data storage is accomplished with IPFS while the Ethereum blockchain guarantees restricted, immutable access to the data. Results indicate SVM and CatBoost provide superior performance with high accuracy. This integrated AI-blockchain approach Cyber threats targeting sensitive IoHT data can be defended with a sophisticated, multi-layered, AI integrated blockchain solution that is secure, scalable, and efficient.

Keywords: IoHT, Artificial Intelligence, IPFS

INTRODUCTION

The Internet of Healthcare Things (IoHT) is crucial to enabling a paradigm shift in contemporary healthcare systems through remote patient monitoring and the access to real-time data. This connectivity, however, exposes systems to critical cybersecurity risks, such as data breaches, unauthorized access, data manipulation, and denial-of-service attacks. Given the sensitive nature of medical data, securing these networks becomes of utmost priority. This project aims to develop an AI-based anomaly detection system that utilizes blockchain and IPFS technologies for secure data management. Cyber threats are identified for IoT datasets with the use of AI models and the data patterns are organized accordingly. Ethereum blockchain has been known for marking data hashes and storing them so any malicious interference with data can be easily detected. Systems that are centralized are more prone to attacks, which is why IPFS is useful as it decentralizes data storage. In unison, the employed technologies provide a flexible structure that can be adjusted to frustrations and problems IoHT data poses, enhancing the privacy, integrity and reliability, while making the

healthcare systems more stable and guarded to attacks.

RELATED WORK

Kumar et al. (2023) designed an Intrusion Detection System (IDS) for the IoT environment with the use of machine learning algorithms. Their model's effectiveness was limited due to real-time responsiveness and required constant changes to be useful. Naveed et al. (2022) developed a network-based anomaly detection system tailored for smart IoT device traffic. Although it was useful for security, its ability to identify unauthorized access was hindered by a significant number of false positives. AI-based anomaly detection for IoHT networks was applied by Ashraf et al. (2020). Their work greatly enhanced detection accuracy, but they faced difficulties with scalability for large hospital networks. Shahin et al. (2022) presented an industrial IoT hybrid model utilizing a hybrid learning paradigm powered by a combination of multiple machine learning paradigms for anomaly detection. While it improved detection accuracy, it was still necessary to validate it on large datasets to prove its robustness. Tareq et al. (2022) studied the deep learning approaches for IoT cybersecurity. Their system could efficiently resolve complex attack pattern recognition, but the high processing demand made real-time response difficult without substantial hardware investment.

TABLE1. Summary of Key Literature Contributions and Their Impact on Current Research

Author	Contribution	Impact on Research
Kumar et al. (2023)	Machine Learning-based IDS for IoT	Introduced adaptive ML for IoT; lacked real-time robustness
Naveed et al. (2022)	Traffic-based anomaly detection in smart IoT	Highlighted network monitoring; high false positives
Ashraf et al. (2020)	AI models for anomaly detection in IoHT	High accuracy; lacked scalability in deployment
Shahin et al. (2022)	Hybrid learning models for anomaly detection	Improved detection rate; required validation on big data
Tareq et al. (2022)	Deep learning for IoT cybersecurity	Accurate detection; hindered by computational complexity

PROPOSED APPROACH

This project presents an intelligent anomaly detection system integrated with blockchain, aimed at securing the Internet of Healthcare Things (IoHT) by employing a multi-layered cybersecurity framework. The AI subsystem is designed to continuously monitor the network and identify intrusions in passive real-time, preserving the integrity and confidentiality of healthcare data. Data from IoT sensors is collected and then uploaded to the InterPlanetary File System (IPFS), where the system generates a unique content-based hash. This hash is then permanently stored on the Ethereum blockchain using smart contracts, thus establishing a tamper-proof audit trail. During data retrieval, the system checks if the alteration the data was subjected to is close to the expected range, which safeguards data claiming. AI algorithms like SVM, Random Forest, CNN1D, and CatBoost in the meantime evaluate the IoT data and classify it as normal or anomalous. These models use labeled datasets such as TON_IoT to achieve peak accuracy in recognizing attack signatures. The combination of blockchain and IPFS offers a decentralized and

unchangeable record system. Moreover, AI models improve real-time threat detection. This blend fortifies IoHT systems by eliminating many single points of failure, automated threat response, reliable access control, and increasing system security.

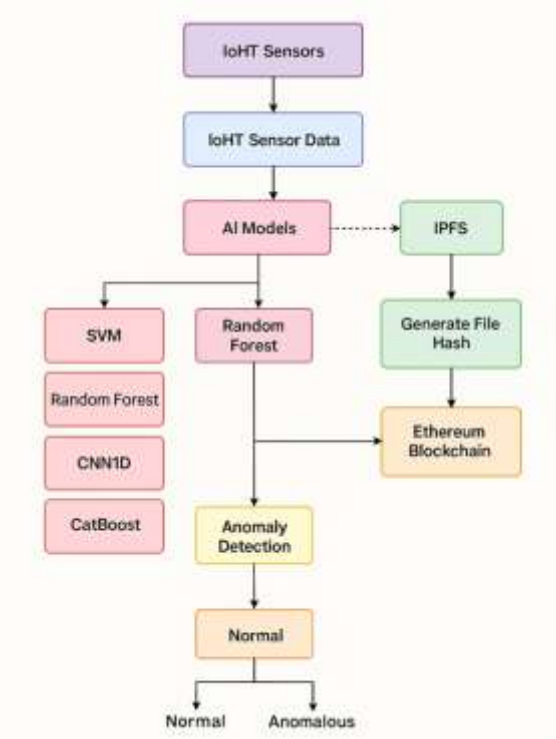


Figure 1: Proposed anomaly detection model

METHODOLOGIES

The methodology of this project is structured into three primary phases: data handling with IPFS and blockchain, machine learning model training, and anomaly detection evaluation.

Phase 1: Secure Data Storage

IoHT sensor data is initially stored in the IPFS, a peer-to-peer distributed file system. The file hash generated by IPFS serves as a unique content identifier and is stored on the Ethereum blockchain using a smart contract. This ensures data immutability and allows secure access retrieval using the stored hash.

Phase 2: Data Preprocessing and Model Training

The dataset, obtained from TON_IoT (specifically weather sensor data), undergoes preprocessing steps like label encoding and normalization. Irrelevant fields such as timestamps are transformed into numerical values, and missing data is handled appropriately. The dataset is then split into training and test sets in an 80:20 ratio.

AI models used include:

- **SVM (Support Vector Machine)**: effective in classifying high-dimensional data.
- **Random Forest**: ensemble technique using multiple decision trees.
- **Gradient Boosting**: enhances predictive accuracy using sequential training.
- **CNN1D**: deep learning model for temporal sequence detection.
- **CatBoost**: powerful for categorical data classification.

Phase 3: Evaluation

Each model is evaluated using accuracy, precision, recall, and F1-score. Visualization of confusion matrices and prediction outcomes provides insights into detection performance.

This layered methodology ensures secure storage, accurate classification, and comprehensive evaluation of anomaly detection in IoHT systems.

RESULTS

The anomaly detection models were evaluated on the preprocessed IoHT dataset using key performance metrics: accuracy, precision, recall, and F1-score. Among all models tested, Support Vector Machine (SVM) and CatBoost delivered the most promising results.

SVM demonstrated high accuracy (97%) and a strong F1-score, indicating its effectiveness in differentiating between normal and attack patterns. Its linear kernel provided optimal separation in high-dimensional feature space.

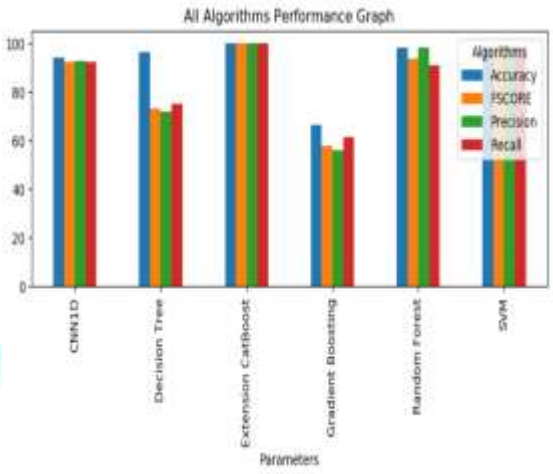
CatBoost, known for its ability to handle categorical data without extensive preprocessing, achieved 100% accuracy and F1-score. Its performance remained consistent across multiple test runs, proving its robustness.

CNN1D, a deep learning model, also showed strong results with over 95% accuracy. However, it required more computational resources compared to classical models.

Other models like Random Forest, Decision Tree, and Gradient Boosting performed well but showed slight drops in recall, leading to a few missed anomalies.

The system successfully integrated blockchain and IPFS for tamperproof data storage. The hash verification mechanism worked seamlessly, identifying any data modification attempts. Visualizations of attack type distributions and model performance comparisons further validated the approach.

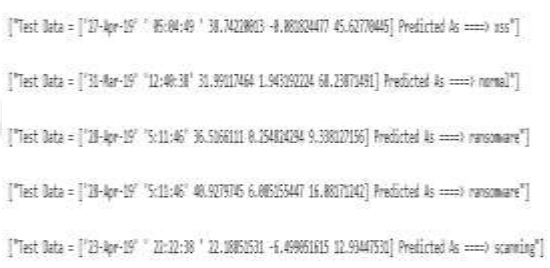
Overall, the combination of CatBoost with blockchain-IPFS architecture offers a secure and accurate anomaly detection solution for IoHT systems.



All Algorithms Performance Graph

	Algorithm Name	Accuracy	Precision	Recall	FSCORE
0	SVM	98.764646	98.889652	98.765275	98.769585
1	Random Forest	98.127866	98.210646	91.147753	93.862893
2	Decision Tree	96.472236	72.031456	75.000000	73.416503
3	Gradient Boosting	66.543556	55.837877	61.241283	57.644693
4	CNN1D	94.370861	92.985501	92.456383	92.589885
5	Extension CatBoost	100.000000	100.000000	100.000000	100.000000

All Algorithms Performance Table



Attack Detection

DISCUSSION

The results of this project affirm the viability of integrating artificial intelligence and blockchain

technologies for robust cybersecurity in IoHT systems. The proposed system effectively addresses two major concerns: real-time anomaly detection and secure, tamperproof data storage.

The use of IPFS in conjunction with Ethereum blockchain ensures decentralized and immutable storage. Even if a data source is compromised, the hash mismatch alerts administrators to potential tampering. This eliminates the single point of failure typical in centralized healthcare systems.

AI models, especially CatBoost and SVM, demonstrated high accuracy and consistency, making them suitable for detecting nuanced patterns in healthcare IoT data. Their efficiency enables deployment in real-time applications where early threat detection is critical to patient safety.

However, computational overhead remains a consideration, particularly with CNN1D models. Resource-constrained devices may require optimization or edge-computing support for seamless integration.

The modular design of this system enables scalability. More IoHT devices and data sources can be added without restructuring the existing framework. Additionally, the model's adaptability to different datasets makes it flexible across various medical contexts.

This discussion highlights the balance achieved between security, scalability, and real-time responsiveness, making the proposed approach a strong candidate for next-generation IoHT cybersecurity frameworks.

CONCLUSION

This project presents a secure and intelligent anomaly detection framework for the Internet of Healthcare Things (IoHT), addressing the growing cybersecurity concerns in connected medical environments. By combining blockchain, IPFS, and AI-based models, the proposed system provides a tamperproof, decentralized solution for real-time threat detection.

CatBoost and SVM emerged as the top-performing models, offering high detection accuracy and reliability. The Ethereum blockchain ensured immutable data storage, while IPFS enabled efficient data retrieval with decentralized control. The system’s smart contracts also facilitated secure and automated data handling.

The integration of these technologies provides a powerful toolkit for combating evolving cyber threats in healthcare systems. Furthermore, the solution’s scalability, transparency, and accuracy make it suitable for broader adoption in real-world applications.

Overall, the framework enhances trust and security in IoHT, offering a proactive defense mechanism that aligns with modern healthcare data privacy and integrity requirements.

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