The Advancements of Blockchain and Artificial Intelligence in the Medical Field

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**Abstract.** The convergence of blockchain and artificial intelligence is revolutionizing the healthcare industry, providing transformative solutions to long-standing challenges. The healthcare sector generates a large amount of sensitive data every day, such as electronic health records, medical imaging, genomic information, and real-time monitoring data, while traditional centralized systems face many challenges in terms of efficiency, security, and data silos. Blockchain ensures the security and transparency of medical data through decentralized architecture, immutability, and encryption protocols. Artificial Intelligence (AI) is adept at processing large-scale data for accurate diagnosis, predictive analysis, and personalized treatment. This article explores how blockchain and AI collaboration can significantly improve the efficiency of healthcare services. For example, blockchain-powered Electronic Health Record (EHR) systems combined with AI diagnostic models can accelerate the clinical decision-making process; In the payment system, smart contracts and AI-driven fraud detection improve the accuracy and efficiency of claims. In terms of the pharmaceutical supply chain, converged technology enables full-process tracking, real-time environmental monitoring, and predictive inventory management. In addition, with the help of the federated learning model of the blockchain infrastructure, collaborative AI training in highly sensitive fields such as medical imaging can be realized while protecting privacy. This paper comprehensively analyzes the current situation, advantages, and limitations of blockchain and AI applications in healthcare, and proposes future development directions, such as revocable blockchain structures, privacy protection mechanisms, unified data standards, and global cooperative governance, to promote the establishment of a safer, more efficient, and intelligent healthcare ecosystem.

# INTRODUCTION

In recent years, the combination of blockchain technology and Artificial Intelligence (AI) has been driving profound changes in the healthcare industry, providing innovative solutions to key issues such as data security, privacy protection, interoperability, and intelligent decision-making. Every day, the healthcare industry generates massive amounts of data such as Electronic Health Records (EHRs), medical images, genomic data, patient monitoring information, and more. However, the existing healthcare data management model relies heavily on centralized storage and processing systems, which are susceptible to data breaches, information silos, and inefficient operations. The distributed storage, immutability, and cryptographic security features of blockchain, combined with AI's intelligent data analytics, predictive modeling, and automation capabilities, bring unprecedented opportunities for innovation to the healthcare industry.

Blockchain technology provides a decentralized and secure data storage and sharing mechanism for the healthcare industry [1]. The sensitivity of medical data requires a high degree of privacy protection and integrity protection, and blockchain ensures that data cannot be tampered with or leaked without authorization through cryptographic hash functions, smart contracts, and consensus mechanisms. Its distributed ledger structure allows for the secure sharing of patient data between healthcare organizations, avoiding information asymmetry caused by data silos, thereby improving the quality of patient care. In addition, smart contracts can automate data access management, ensuring that medical data is only accessed if compliance conditions are met. For example, patients can autonomously authorize research institutes or doctors to use their data through smart contracts on the blockchain without fear of data misuse. In addition, the traceability feature of blockchain can create a complete audit trail of medical data, ensuring that all data modifications and access records are clearly visible, improving transparency and trust in the healthcare industry.

Artificial intelligence has shown great potential in the healthcare industry, especially in disease prediction, medical image analysis, personalized treatment, and drug discovery [2]. AI models can efficiently process and analyze large amounts of complex medical data, identify disease patterns that human doctors may ignore, and improve the accuracy of diagnosis. For example, deep learning models can detect cancer cells in medical images, helping doctors make more accurate judgments. However, the application of AI in the healthcare industry faces challenges in data availability, quality, and privacy protection. Because medical data is often concerned with patient privacy and is heavily regulated by regulations such as General Data Protection Regulation (GDPR) and Health Insurance Portability and Accountability Act (HIPAA), data sharing is limited, impacting the effectiveness of AI training. Blockchain technology can enable secure data sharing while ensuring privacy protection, thereby promoting the in-depth application of AI in the medical field [3].

At present, AI and blockchain technology are making the medical industry more intelligent and efficient, and the achievements in this regard include blockchain and AI to improve the efficiency of medical services [4], and because of the cryptocurrency application attributes of blockchain [5], AI-blockchain technology can also improve the medical payment system, and the decentralized nature of blockchain and the automatic regulation function of AI can be used to manage the pharmaceutical supply chain [6]. Secure data sharing through federated learning and AI model training enables AI-blockchain technology to analyze patient image reports [7].

The purpose of this paper is to comprehensively analyze the achievements of existing AI and blockchain technologies in the medical field, and discuss the advantages, disadvantages and application prospects of these technologies. The remainder of this paper will be organized as follows: Section 2 will discuss the current technological progress in the blockchain-AI-medical field, Part 3 will discuss in more detail the specific advantages and disadvantages of each part of the technology. Section 4 will summarize the blockchain-AI-medical technology and look forward to the future improvement and application of this technology.

# Method

## Improve the Efficiency of Medical Services

The convergence of blockchain and AI has provided significant progress in improving the efficiency of healthcare services. Blockchain technology, with its decentralized and immutable nature, ensures the secure storage and transparent sharing of medical data. This is critical to improving trust between healthcare providers and patients, as blockchain makes verified patient data accessible in real-time and free from tampering or unauthorized alteration [4]. AI algorithms can quickly process and analyze this data to help make accurate decisions and reduce time-consuming manual processes.

A key area where blockchain works with AI is to streamline the management of patient records and medical records. Blockchain enables medical data to be securely stored and shared among authorized personnel, and AI uses this data to provide predictive analytics for better diagnosis and treatment planning. Having instant access to a patient's comprehensive medical record increases the speed of diagnosis and reduces delays in treatment, which is especially important in emergency care [4].

In terms of improving the efficiency of medical services, Zhang et al. proposed a blockchain-based Electronic Health Record (EHR) system architecture, which uses Ethereum smart contracts to control data access, and combines AI for data analysis to realize the intelligence of the diagnostic support system. The system encrypts the patient's diagnosis and treatment information and stores it on the blockchain, and uses distributed consensus algorithms to ensure that the information cannot be tampered with [8]. The AI part uses a combination of Multi-layer Perceptron (MLP) and decision tree algorithm to classify and predict historical cases and existing symptom data to improve diagnostic efficiency.

In addition, Ahmed et al. used an integrated Deep Neural Network (DNN) to analyze medical records from the blockchain in real time, and used Natural Language Processing (NLP) technology to extract key elements from the doctor's diagnosis text to assist in the formulation of personalized treatment plans [9]. The system allows doctors to access AI-recommended treatment pathways through a blockchain interface and make decisions based on patient history, significantly reducing the time of diagnosis and treatment.

## Optimize the Medical Payment Process

The convergence of AI and blockchain technology has the potential to revolutionize healthcare payment systems by addressing key challenges such as inefficiencies, errors, and security issues. AI's ability to process massive amounts of data and make predictions, combined with the secure and transparent records provided by blockchain, provides a strong foundation for streamlining medical payments [5]. This section explores how these technological convergences can optimize the healthcare payment process.

One of the main advantages of AI in the medical payment system is its ability to automate and speed up payment processing. Machine learning algorithms can analyze payment data, detect anomalies, and identify potentially fraudulent activity, reducing the risk of errors and fraud. By leveraging AI, healthcare providers can ensure more accurate and timely bill processing, reduce delays, and reduce administrative overhead [5]. AI can also help predict payment trends, enabling healthcare organizations to manage cash flow more effectively and improve the accuracy of financial forecasting [5].

In terms of optimizing medical payments, Hussein et al. developed a smart insurance payment platform that combines AI and blockchain. The system leverages blockchain to record insurance contracts and implement event-driven smart contract logic, such as triggering payment contracts for patient →visits, such as triggering payment contracts for patient visits, to automatically initiate the payout process. The AI module uses reinforcement learning algorithms to analyze historical claims data and identify fraud, effectively improving the speed and accuracy of claims settlement [10].

In addition, Khan et al. implemented an AI model combining K-means clustering and logistic regression to predict claims anomalies, and the model results were jointly verified by the IPFS distributed file system and the blockchain consensus mechanism to ensure that the data in each claim process is tamper-proof and auditable throughout the process [11].

## Pharmaceutical Supply Chain Management

The convergence of blockchain and AI has significant advantages in optimizing pharmaceutical supply chain management. Blockchain provides a decentralized ledger that ensures data immutability and transparency, which is essential for tracking the production and transportation of pharmaceutical products. This technology minimizes the risk of counterfeit medicines by providing real-time access to verified drug information for all stakeholders, from manufacturers to distributors and retailers.

AI complements blockchain by optimizing inventory management and demand forecasting. AI can analyze vast amounts of data on drug supply and demand trends, helping pharmaceutical companies predict future demand and adjust production or inventory accordingly. This leads to more accurate inventory management, reducing the risk of drug shortages or expirations [6].

The integration of blockchain and AI in pharmaceutical supply chain management not only improves operational efficiency but also ensures greater security and transparency. This convergence solves issues such as counterfeit medicines, inefficient inventory management, and lack of real-time tracking, paving the way for more reliable and cost-effective pharmaceutical logistics [6].

In order to solve the management problem of the drug supply chain, Wang et al. built a drug tracking system combining blockchain and AI. The system uses Hyperledger Fabric as the underlying platform, combined with Internet of Things (IoT) devices to collect real-time information such as drug temperature and humidity, transportation time, etc., and records each step of the logistics process through blockchain to achieve traceability. Each transaction data is encrypted by SHA-256 and then written into the chain to ensure data integrity [12].

The AI part is based on time-series forecasting models to forecast drug demand and inventory levels to optimize supply planning. In addition, by using cluster analysis to identify possible bottleneck areas in the drug distribution process, the optimal scheduling of transportation routes can be realized. This fusion technology has been successfully applied in the distribution of COVID-19 vaccines, significantly reducing the risk of delivery delays and counterfeit medicines and improving logistics responsiveness and drug safety [13].

## Patient Imaging Examination

The convergence of blockchain technology and AI has significant potential to improve patient image analysis, especially in the diagnosis of COVID-19 tests such as CT scans [7]. Traditional approaches to medical imaging often rely on centralized data collection and analysis, which presents challenges with privacy concerns and inefficiencies in data storage and sharing. By combining blockchain and AI, these issues can be mitigated, providing a more efficient and secure way to process patient image data [7].

In terms of medical image analysis, Sun et al. proposed a distributed AI model training system that combines federated learning and blockchain. The system uses CNNs to identify lung lesions in CT images of COVID-19 patients, and model training is completed locally by each medical institution, only uploading encrypted gradient information to the blockchain to achieve model parameter aggregation and using Elliptic Curve Encryption (ECE) to ensure data transmission security [14].

In order to further protect data privacy, the system uses Homomorphic Encryption technology to encrypt the model update and verifies the legitimacy of the uploaded model parameters through the blockchain smart contract. All training logs and model iteration processes are recorded on the blockchain, making the whole process auditable and tamper-proof.

This method shows high accuracy and high privacy protection ability in multi-agency collaborative training and is especially suitable for AI analysis of highly sensitive data such as pathological images.

# Challenges

## Data Privacy and Regulatory Compliance Challenges

The convergence of blockchain and AI in the medical field aims to solve problems such as data fragmentation, privacy protection, and system inefficiencies. However, interfacing these technologies with stringent regulations such as the General Data Protection Regulation and the Health Insurance Portability and Accountability Act presents significant technical hurdles [15]. These regulations require data minimization, user consent, and the right to data deletion, and these principles are in natural conflict with the "immutable" nature of blockchains.

Technically, blockchain is an immutable and append-type ledger structure, and once data is written, it cannot be modified or deleted, which directly violates the "right to be forgotten" proposed by the GDPR. The current mitigation is to only store data hashes or encrypted references on-chain, but this metadata may still be considered "personal data" in some contexts and still subject to regulatory compliance.

Federated Learning (FL) is a privacy-preserving decentralized AI training method, but its shared model updates can also be subject to model inversion or gradient leak attacks. For this reason, methods such as differential privacy and secure multi-party computation have been introduced to protect privacy, but these techniques have an additional computational burden and require fine-tuning of parameters to balance model performance and privacy [15].

In addition, FL's integration with blockchain adds to the protocol complexity. Smart contracts are responsible for verifying the integrity of model updates, managing identities, and recording metadata, which leads to increase on-chain transactions and higher latency. Especially in the public chain, the problem is more prominent; While private chains are in control, they may weaken decentralization.

Ultimately, healthcare is a multinational, multi-jurisdictional industry, and the system needs to be able to adapt to different legal frameworks. At this stage, the lack of technical standards to support this kind of compliance adaptation makes the integration of blockchain and AI prone to legal challenges and technical deadlocks.

## High Cost and System Complexity

The integration and deployment of AI and blockchain into the medical system requires a large amount of financial and technical resources [16]. From model training, blockchain consensus mechanism, to data encryption and communication protocols, each module requires independent high-performance equipment and personnel collaboration, which is extremely costly.

In terms of AI, deep learning models commonly used in image diagnosis and predictive analysis, such as CNN or Transformer structures, require GPU clusters and high memory support. On the blockchain side, the concurrent operation of smart contracts and cryptographic operations can cause resource competition and processing bottlenecks, especially in real-time medical environments.

Many blockchain platforms use consensus mechanisms such as Proof-of-Work, which have low throughput and high latency, and even if they use protocols that are more suitable for private chains, such as PBFT, the number of participating nodes will also experience performance degradation [16].

At the same time, in order to protect data security, mechanisms such as zero-knowledge proof, elliptic curve encryption and homomorphic encryption are introduced, which can enhance security, but also significantly increase the burden on the system and reduce the operation efficiency.

Docking with traditional hospital information systems is also a major challenge. Many hospitals still use outdated systems with a lack of APIs and cryptographic interfaces, requiring the development of middleware, protocol converters, and data standardization modules, increasing implementation time and maintenance costs.

Deploying such a system would also require a multidisciplinary team, including cryptographic engineers, AI specialists, medical informatics specialists, and more, and it would be costly to organize cross-domain collaboration. For agencies with limited resources, this deployment is overwhelming.

## Blockchain Storage and Scalability Limitations

Blockchain is not designed to be optimized for the large-scale, high-frequency data environment of healthcare, especially when dealing with electronic medical records, genomic data, and medical imaging [17].

It is often not feasible to write complete data on-chain, especially for high-resolution CT or MRI images, which can easily run into hundreds of megabytes per file. If it is directly deposited into the blockchain, not only will the network be congested, but also the storage cost and confirmation time will be greatly increased. As a result, most systems employ off-chain storage and only write hashes or indexes on-chain. However, this introduces a dependency on off-chain systems and reduces the overall level of decentralization of the system [17].

Scalability is also a major technical hurdle. Most public blockchains can only process a few dozen transactions per second, which is far lower than the real-time or quasi-real-time requirements of medical environments, such as ICU monitoring, emergency treatment, etc. While Layer 2 technologies and sharding schemes have been proposed to optimize performance, they are still in the development or experimental stages and may introduce new security vulnerabilities and synchronization issues.

Even with efficient consensus algorithms such as PBFT, it can cause delays as the number of nodes increases. This is prone to performance bottlenecks when multiple hospitals share records simultaneously.

In addition, smart contracts on the blockchain need to maintain determinism and simplicity, limiting the complexity of AI-related calculations. This makes it impossible for many AI models to update or inference logic to be executed directly on-chain, limiting the utility of the system.

## Limited Generalizability of AI Models

AI models are often limited by training data, making it difficult to generalize across different hospitals, devices, or populations. This problem of "migration failure" is particularly acute in federated learning environments [18].

In federated learning, there are huge differences in the data of each participating node (non-IID), which leads to inconsistent model update directions, and it is difficult to form a unified high-performance model. Without a personalized optimization mechanism, such as an adaptive layer or a custom optimizer, the final model may perform well in some nodes but poor in others.

In addition, there are inconsistencies in the data formats, coding systems, and image equipment standards used by different hospitals, and complex data cleaning and standardization processes need to be developed. Each preprocessing step can introduce errors, reducing the reproducibility and reliability of the model.

The problem of interpretability of AI models is also prominent. Deep neural networks are often "black boxes" that lack traceable logical paths that are not conducive to clinician understanding and trust. Although blockchain can record the data provenance process, it does not directly improve the transparency of the model [19].

In the distributed environment, the lack of unified verification standards and evaluation mechanisms makes it difficult to evaluate the reliability of the model, which affects its deployment and approval in the medical system.

# Future Prospects

Revocable blockchain architectures can be used to technically support data "tombsizing" under certain conditions to meet the GDPR's "right to be forgotten" [20]. At the same time, the differential privacy mechanism and secure multi-party computation are introduced for the encrypted exchange of model parameters to strengthen the compliance capability of the federated learning system.

In addition, there is also a trend to develop smart contract frameworks with legally configurable capabilities. Through preset compliance rule templates, adapt to medical data regulations in different countries/regions, so as to achieve data sharing compliance in multiple jurisdictions

In order to alleviate the problem of data heterogeneity, the use of unified medical data standards and cross-institutional ontology mapping tools is promoted to make the data structure consistent before AI training [21].

At the same time, a cross-border collaboration platform will be established to promote policy coordination and technical standard formulation of medical AI and blockchain [22]. It is recommended to cooperate with international organizations such as ISO, IEEE, and HL7 to develop a unified audit format, interface specification and model verification framework for AI blockchain systems.

It is also necessary to develop an AI ethics and compliance engine to conduct automatic bias detection and decision-making path review before system deployment, so as to assist developers in avoiding algorithmic bias and regulatory risks.

# Conclusion

The convergence of blockchain and AI is reshaping the healthcare landscape like never before, revolutionizing operational efficiency and patient-centric service delivery. From blockchain-powered EHR systems to improve diagnostic efficiency, to smart contracts automating insurance claims, to supply chain drug tracking and medical image privacy analysis, the combination of the two plays a key role in multiple healthcare subsystems.

The immutability, decentralization and transparency of blockchain have established a trustworthy sharing framework for medical data. At the same time, AI's powerful data processing and prediction capabilities make medical services more accurate, timely, and personalized. Together, they optimize medical processes, reduce administrative burdens, and improve decision-making accuracy.

However, the actual deployment of this convergence still faces legal compliance challenges, such as the "right to be forgotten" proposed by the GDPR, which is contrary to the permanent storage mechanism of the blockchain. In addition, high computational costs, technical complexity, and limited scalability are also practical obstacles; The weak generalization ability of federated AI models under data diversity and the lack of unified standards also affects their deployment and supervision.

To solve these problems, it is necessary to develop a blockchain architecture with an undo mechanism, a differential privacy and compliant smart contract system. At the same time, it promotes the unification of medical data standards, the formulation of interface specifications, and the cooperation of international organizations.

In short, although the integration of blockchain and AI in healthcare is still in the exploratory stage, it is expected to build a smarter, safer, and fairer future healthcare system through technological innovation, policy coordination, and interdisciplinary cooperation.

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