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Exploring Research Challenges of Blockchain and Supporting Technology with Potential Solution in Healthcare

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Abstract: The healthcare industry is currently experiencing a digital revolution driven by developments in information technology. This transformation is geared to improve health care, diagnosis, and continuous surveillance by utilizing smart devices. The combination of Blockchain and artificial intelligence technologies poses numerous research challenges that require comprehensive investigation. The objective of the study is to conduct an early investigation into blockchain-based artificial intelligence approaches. Afterward, it seeks to recognize and address certain unresolved research challenges that must be addressed in the future. The occurrence rates for achieving scalability, interoperability, and managing power consumption are 19%, 24%, and 28% respectively. The research work suggests that the problem of excessive energy usage and low transaction rates can be eliminated by improving the consensus algorithms as the efficiency of both of these depends on it. The scalability issue may be resolved in the future using forks and sharding techniques and as far as regulatory issues are concerned the government must set up common policies to follow.

Keywords:: Blockchain, Artificial intelligence, Deep learning, Healthcare, Health, Machine learning, Challenges

1. INTRODUCTION

Artificial intelligence (AI) has experienced substantial advancements and progress specifically in healthcare. Concurrently, recent developments in blockchain technology have presented novel opportunities for decentralized ecosystems. The COVID-19 epidemic has brought attention to the urgent necessity of timely information, recognizing that the conventional healthcare system, which primarily focuses on patients and hospitals, is becoming increasingly obsolete. The utilization of mobile healthcare has experienced a significant increase, notably due to the modern techniques like Internet of Medical Things (IoMT), which facilitates the remote tracking and monitoring of diverse health issues using smart devices [1][2]. Although this technology provides improved convenience and reliability, it also generates and transmits significant amounts of medical data that require protection [3][4]. Fig.1 depicts the intricate relationship between Artificial Intelligence (AI) and Blockchain technology, showcasing the seamless data transfer from IoT devices to smart applications. These applications utilize blockchain and machine learning models to conduct a thorough analysis and make accurate predictions.

Blockchain, initially developed to serve as the foundation for the Bitcoin ecosystem, has been successfully applied in various fields, providing unparalleled levels of security [5]. Significantly, the healthcare sector has started to incorporate blockchain technology in multiple aspects of the digital age. The functionalities it offers, including decentralized exchanges, consensus and smart contracts, are designed to protect the privacy of sensitive health information owned by patients, who have a crucial position in the healthcare industry. The dataset includes several types of information, such as patient health and trial outcomes, payment records, medical reports, and additional data [6]. All the abbreviations used in this study are illustrated in Table I.

The study organized as section 2 provides an overview of the current state-of-the-art for blockchain and AI. Sections 3 and 4 outline the contribution of the study and methodology respectively. Section 5 discusses the background of blockchain and section 6 elaborates on the analysis and summary of AI-based techniques. Section 7 showed the integration of AI with blockchain applications. Moreover, open research challenges and possible solutions are discussed in section 8. Finally, section 9 discusses the findings of the study and section 10 concludes the study and outlines further work.

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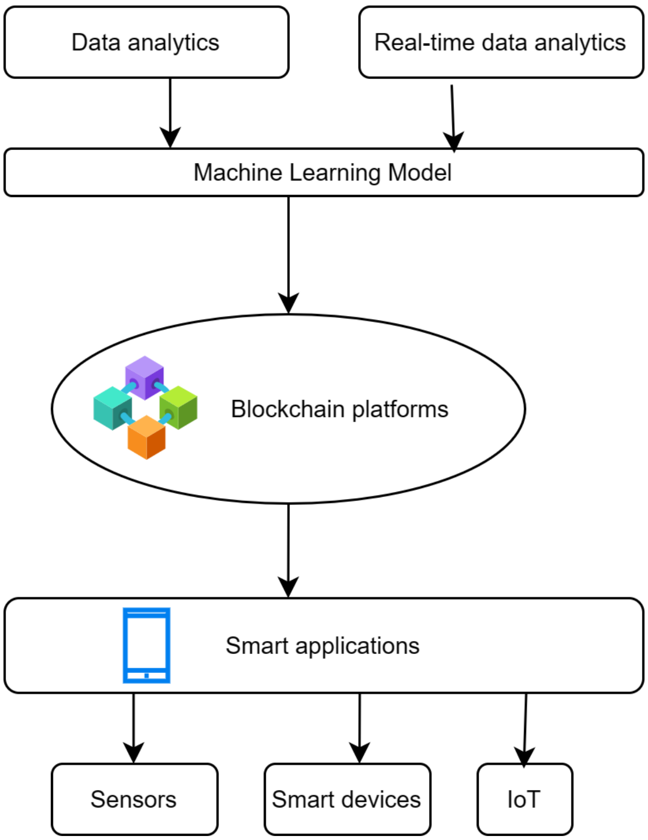

Figure 1. AI integration with blockchain

TABLE I. Used abbreviations

Acronyms	Description
AI	Artificial Intelligence
IoT	Internet-of-things
BCT	Blockchain Technology
NLP	Natural Language Processing
ML	Machine Learning
EMR	Electronic Medical Records
DL	Deep Learning
CNN	Convention neural network
P2P	Peer to Peer
EHR	Electronic Health Record
BTC	Blockchain transaction counter
ANN	Artificial Neural Network
ECC	Elliptic curve cryptography

2. Literature Review

The integration of blockchain and supporting technologies like artificial intelligence in the healthcare sector presents promising opportunities for improving data security, interoperability, and overall efficiency. However, numerous research challenges hinder the widespread adoption and implementation of these technologies. Therefore, there is a need to explore these challenges comprehensively and propose potential solutions to address them, thereby facilitating the effective utilization of blockchain and supporting technologies to enhance healthcare systems. This research work contributes towards highlighting such issues and then proposing potential solutions by reviewing published studies comprehensively.

Many researchers have conducted comprehensive and cutting-edge research on blockchain and AI. The effect of a publication is determined by the number of citations it receives. Hence, to gain insight into the scientific dynamics of the discipline, we examine the most influential papers in the context of blockchain-based AI in the healthcare domain. Table II illustrates the highest cited articles and also presents the summary of the prior art. The results displayed that the article [7] disclosed a detailed review of IoT, AI, and blockchain in Covid-19 reaching 769 total citations and 192 total citations per year. Furthermore, the authors introduced a tool that empowers patients with control over their health data by utilizing blockchain and deep learning techniques [8].

Researchers designed a healthcare system by employing Blockchain 3.0 with Healthcare 4.0 and addressing real-world healthcare challenges. The authors also presented a comprehensive survey of blockchain-based smart healthcare systems. For implementation, they wrote the smart contract in solidity language. Simulation results of the proposed study demonstrated an efficient performance, with Gas value within Ethereum limits and automated smart contract execution below 20 seconds, showcasing the viability of the proposed system [9]. Similarly, the research implemented a conceptual framework for securely exchanging the patient data and providing access control to the patient. It also introduced a machine learning-based model for control over the data quality [10]. The author utilized blockchain in healthcare for a COVID-19-safe clinical practice and leveraged artificial intelligence for a generalizable predictive system. A SWOT study evaluates the implementation of a blockchain-based prediction system and highlights the constraints for controlling the risks associated with SARS-CoV-2 infection [11]. The researchers provided a detailed categorization and grouping of federated learning applications across several techniques like AI, IoT, blockchain, and natural language processing. This analysis was conducted exclusively within the contexts of healthcare and education [12].

A proposal was made to implement a private blockchain and IoT-based application for drone-assisted healthcare ser-

TABLE II. Citation per article

Ref	Year	Contribution	Blockchain	AI	IoT	Total Citation	Total Citation per Year
[7]	2020	Presented a detailed review on IoT, AI and blockchain in Covid -19	Y	Y	Y	769	192.25
[8]	2018	Introduced a tool that empowering the patients control	Y	Y	N	302	50.33
[9]	2020	Designed a healthcare system by employing Blockchain 3.0 with Healthcare 4.0	Y	N	N	151	37.75
[10]	2018	Implemented a conceptual framework for securely exchanging the patient data and providing access control to the patient	Y	Y	N	141	23.50
[11]	2020	Proposed a blockchain-based prediction system and highlights the constraints for controlling the risks	Y	Y	N	88	22.00
[12]	2022	Explored categorization and grouping of federated learning applications	Y	Y	N	82	41.00
[13]	2020	Implemented a private blockchain and IoT-based application for drone-assisted healthcare services	Y	N	Y	49	12.25
[14]	2021	Presented a telesurgery method that combines blockchain and AI technologies	Y	Y	N	46	15.33
[15]	2022	Designed a secure medical data transmission and diagnosis model named BDL-SMDTD	Y	Y	N	44	22.00
[16]	2022	Suggested an effective healthcare system by employing blockchain and an Intrusion Detection System (IDS) to recognize and identify malicious activity	Y	N	Y	43	21.50
Proposed study	2024	This article presents a comprehensive review of integrating blockchain and supporting technologies into healthcare systems.	Y	Y	Y	-	-

vices. These services include duties like collecting blood and urine samples and delivering medicine. The purpose of this framework was to mitigate potential vulnerabilities like replay and man-in-the-middle attacks that may arise from wireless communication in the healthcare setting [13]. To address the difficulties faced by real-time AI-driven telesurgery systems like security, efficiency, dependability, trust, and transparency, the researchers have presented a telesurgery method that combines blockchain and AI technologies, specifically intended for 6G networks. BATS employed unmanned aerial vehicles (UAVs) to transfer healthcare products during surgical procedures, efficiently avoiding road traffic jams. The findings include excellent predictive accuracy, increased efficiency as the number of users grows, little data loss, cost-effective storage, profitable data extraction, and optimized bandwidth use [14]. The authors implemented a secure medical data transmission and diagnosis model named as BDL-SMDTD. Researchers employed a technique called MFO-ECC, which combines moth flame optimization with ECC. The proposed BDL-SMDTD demonstrated high classification performance, including sensitivity, specificity and accuracy of 96.94%, 98.36%, and 95.29% respectively. The model utilized feature extraction techniques based on ResNet-v2 [15].

In another study, authors suggested and implemented an effective healthcare system by employing blockchain and an

Intrusion Detection System (IDS) to recognize and identify malicious activity. The suggested approach allows clinicians to continuously monitor patients using medical sensors and provide periodic predictions about diseases. The results demonstrate that for disease prediction, the recommended system obtained an accuracy of 93.22%, while the RTS-DELM-based system achieved an accuracy of 96.18% in intrusion detection estimation [16]

3. Contribution of The Study

• This study explores the existing literature that discusses the integration of AI with blockchain. • It provides a detailed evaluation of contributions made by AI and blockchain technology in the advancement of the healthcare industry. • The main purpose is to offer readers an understanding of the approaches and algorithms used for blockchain-based AI applications, the challenges of associating AI with blockchain, and all the possible solutions for them.

4. Methodology

To determine the most significant research on AI and Blockchain technology, follow the PRISMA technique which is a globally acknowledged and recommended methodology for performing Systematic reviews and Meta-analyses. To accomplish the comprehensive review effectively, it is imperative to identify all the articles, thereby bolstering the evidential foundation. Hence, diverse parameters are employed to encompass relevant articles while excluding irrelevant ones from the entire pool of research literature, as depicted in Table **??**III. Conducting a thorough and authentic comprehensive review necessitates the identification of relevant articles and the exclusion of unsuitable ones. Discerning acceptable research articles entails a complex process that can be established by adhering to appropriate methodologies as depicted in Fig. 2.

The timeframe considered spans from 2018 to 2023, encompassing five years. Initially, the search employs keywords such as 'blockchain,' 'artificial intelligence,' and 'research challenges' in conjunction with 'healthcare,' utilizing Boolean operators 'OR' and 'AND' to refine the search criteria. Papers are selected based on titles, keywords, abstracts, and conclusions. A total of 511 articles are identified from reputable sources such as IEEE, Google Scholar, ACM Digital Library and Science Direct. Papers in languages other than English, not scientific and those not include the keywords are disregarded. After removing all the duplicate records 131 articles remained. A full-text review was performed on all the fully accessed articles. Finally, 75 articles were included in this review.

5. Blockchain Technology

Blockchain technology serves as the fundamental basis for modern cryptocurrencies, deriving its name from its substantial dependence on cryptographic operations. The utilization of a blockchain for facilitating Bitcoin transactions was initially proposed by Satoshi Nakamoto in 2008.

TABLE III. Articles selection and exclusion criteria

Inclusion	Exclusion
The articles must be authored in English.	Omitted multi-lingual and not scientific articles from consideration.
The title and abstract should clearly define the proposed work.	Research articles unrelated to healthcare are promptly eliminated.
Publications should be recent.	Duplicate articles received from different sources are removed.
The research work's details should be thoroughly elucidated.	The articles with unknown journals and conferences have been suspended.
The articles should be published in reputed journals by established publishers.	Articles lacking clear objectives in their publication have been disregarded.

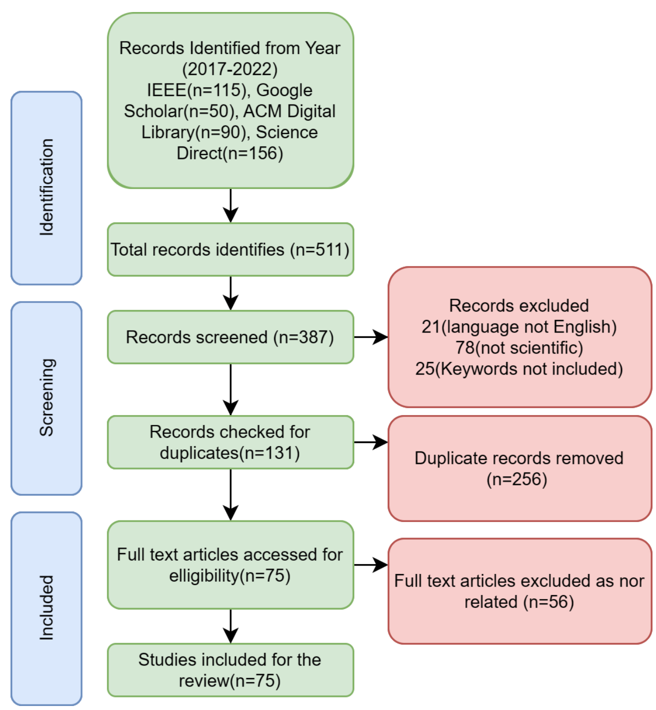

Figure 2. Prisma flowchart for review

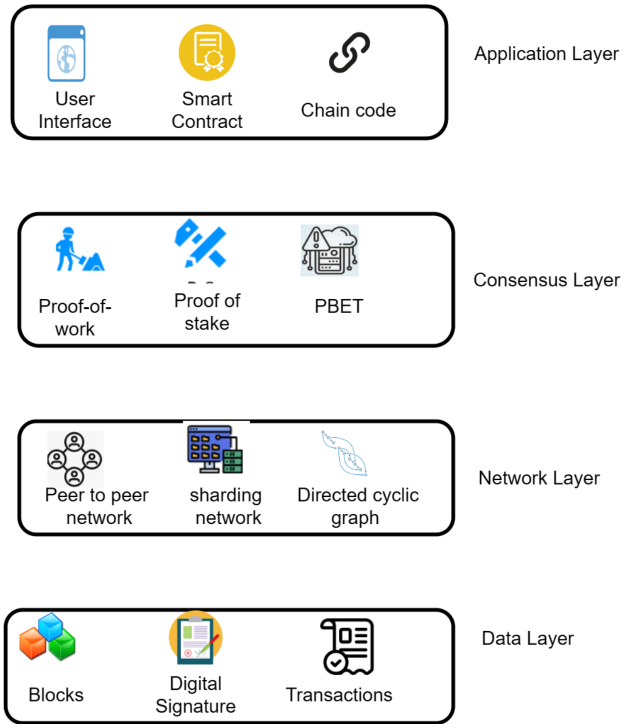

Figure 3. Blockchain Layered Architecture

This technology enables decentralized nodes to facilitate the transfer of digital assets without the need for middlemen [17].

Blockchain architecture includes many layers similar to the TCP/IP model [17][18] as shown in Fig.3. Blockchain is structured into four layers, each with a distinct function [19]. The data layer in the blocks manages and organizes all the data. Different Blockchain networks use different techniques for storing and organizing data. Blockchain stores data in blocks that are linked with each other. The block body and header are the two main components of each block [20][21]. Block body stores all the information for transactions, and BTC (Block Transaction Counter) counts the total transactions within a block. Blockchain header includes block-version, time-stamp, Nbits, Merkle root, block hash, and previous block hash, as shown in Fig. 4 and the description of all these fields is given in Table IVIV. In the chain of the blocks, the very first block is known as the genesis block and the hash address of this block is set to zero since it lacks the preceding hash address, as depicted in Fig. 4.

Network Layer is also known as P2P (Peer2Peer) layer. This layer ensures communication between the nodes. There is no need for a centralized server; every network member has equal legal rights to carry out transactions, access the storage capacity and use the network. This layer maintains both the complete nodes and light nodes. Full nodes handle the mining process and transaction validation and verifica-

TABLE IV. Blockchain Header Key Field Description

Sr. no	Key Field	Description
1	Block version	It is a 4 Byte field that holds the software version number and illustrates which consensus protocol rules should be followed.
2	Timestamp	It is also a 4 Byte field. Timestamp is a Unix timestamp value that represents when this block was created.
3	N-bits	The target threshold value of the block hash is 4 bytes, which miners use to mine a new block over PoW (Proof of Work).
4	Merkle root	Markel tree is a binary hash tree. The root is a 32-byte field used to diagnose the transaction stored in the block.
5	Block hash	It is a hash code of the current block, which consists of 256 bits.
6	Previous block hash	It is a hash code of the block used by block to establish a link with the previous block.

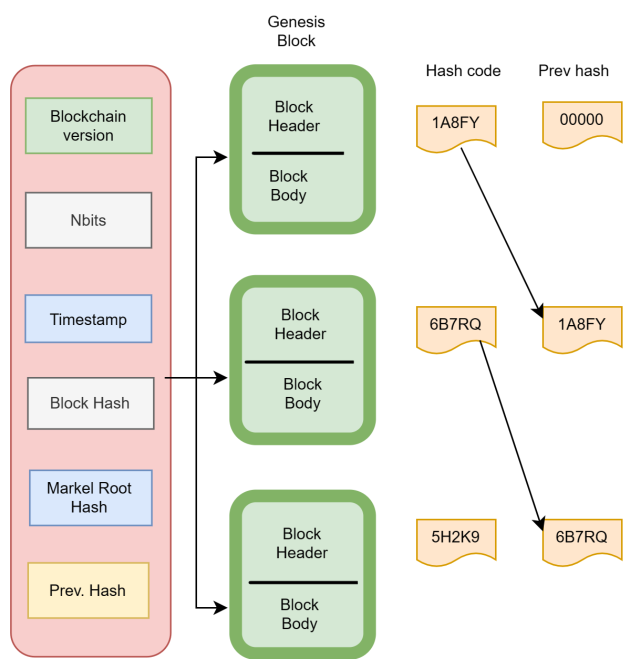

Figure 4. Structure of the Blockchain Header

tion. Light nodes are only responsible for maintaining the Blockchain header. Every node broadcasts the transaction across the network using broad protocols and independently verifies the transactions [22].

Consensus Layer is a crucial component in the layered design of a blockchain. The peer nodes use consensus algorithms to reach an agreement for transaction validation. The consensus mechanism is a mining procedure. Different Blockchain uses different consensus algorithms. For example, in the public blockchain all the miners determine the consensus mechanism in the public while in the private Blockchain, the mining algorithm is determined by only one node. In federated Blockchain, a group of the selected leaders determines the mining process. Table V V illustrates the comparison of different consensus algorithms. The data reveals that traditional consensus protocols tend to have higher power consumption and experience lower transition rates. In contrast, emerging protocols such as Proof of Luck (PoL) demonstrate greater energy efficiency.

Proof of Work has been widely used in cryptocurrencies like Bitcoin and has proven effective in creating decentralized and secure Blockchain networks. However, it has also raised concerns about its environmental impact due to the high energy consumption associated with mining. As a result, alternative consensus mechanisms like Proof of Stake (PoS) have emerged as more energy-efficient alternatives. The efficiency of PoW can be computed based on (1).

$$E = \frac{(cd * TPS)}{T_{gt}} \tag{1}$$

where cd is the confirmation delay, TPS is the number of transactions per second, and Tgt is the time at which a new block will be generated. A block will be added if it satisfies (2) given condition.

$$V_h \leq -1/D \leq 1 \tag{2}$$

where V_h is the gained value of the hash, is the function, and is the target deadlock. First, to calculate the best hash value, compute the i_{th} node mining time as in (3).

$$T_{ith}^{m^{pow}} = \frac{D}{r_i} \tag{3}$$

where r_i is the i_{th} node computation power. Each miner nodes $(n_1, n_2, \ldots, n_i)$ has the corresponding computation power $(r_1, r_2, \ldots, r_i)$ with $(\mathrm{T}_1^{m^{pow}}, T_2^{m^{pow}}, \ldots., T_n^{m^{pow}})$ mining time. The new block generation time will be the minimum from all node mining times, expressed as in (4).

$$T_{gt}^{pow} = min((T_1^{m^{pow}}), T_2^{m^{pow}}, \ldots., T_n^{m^{pow}}) = \frac{D}{(\sum_{i=1}^{n} r_i)} \tag{4}$$

Thus, the block confirmation delay time can be expressed as in (5).

$$T_{cd}^{pow} = n^{pow} * T_{gt}^{pow} \tag{5}$$

where n^{pow} is total number of blocks for which new block wait to confirm. Each block has a limited size; the total number of transactions stored in block cannot exceed block size capacity, B. So, PoW transactions per second can be expressed as in (6).

$$TPS = \begin{cases} \sum_{i=1}^{n} \lambda_i \sum_{i=1}^{n} \lambda_i \leq \frac{B}{T_{gt}^{pow}} \; is\ a\ network\ loadless \\ \frac{B}{T_{gt}^{pow}} \sum_{i=1}^{n} \lambda_i \geq \frac{B}{T_{gt}^{pow}} \; is\ a\ network\ loaded\ scenario \end{cases} \tag{6}$$

The Applications Layer is subdivided into two sub-layers, specifically designed to deliver a brief and accurate description of the results of the experiment, analysis, and the practical implications drawn from the experiments. The front-end layer is responsible for user interaction, while the blockchain technology functions as the backend system. Within this layer, the primary task is to maintain the code required for executing transactions.

6. Analysis and Summart of AI-Based Techniques

Artificial Intelligence refers to the utilization of machines to do tasks that are often associated with human intelligence. Table VI illustrates the summary of blockchain-enabled ML and DL techniques. ML enables computers to acquire knowledge and derive inferences from data without the need for explicit programming [37]. Advances in ML and DL systems have significantly improved their abilities as well as expanding the scope of potential uses in several fields like computer vision, text and picture analysis. [38]. Contemporary applications commonly integrate machine learning and deep learning techniques to varied extents. It is worth noting that the healthcare industry has widely adopted the integration of AI within several sectors. Fig.5 illustrates the diverse applications of AI in the healthcare field.

Efforts are being made to merge the functionalities of AI with Blockchain to establish a resilient and intelligent system. This system aims to unite the privacy advantages inherent in BCT with the accurate accuracy facilitated by AI. Enhancement of relevance in the medical sector requires the integration of several elements including data analysis, diagnosis, verification of health reports, and decision-making. The suggestion has been made that combining decentralized AI with BCT could enhance its influence within the medical field [53]. This section offers an in-depth review of the different techniques and methods utilized for the integration of AI and BCT in the healthcare domain. AI-based blockchain techniques are separated into two distinct categories as shown in the Fig. 6: Machine Learning and Deep Learning. Fig. 7: illustrates the yearly increase in publications based on the SCOPUS database, specifically in the field of blockchain-based machine learning and deep

TABLE V. Comparison Between Various Consensus Algorithms

Consensus algo-rithms	Type	Structure	Scalability	Security	Fee	Time	Speed (tps)	Trust Level	Platform	Ref.
PoW	Public	Power full	Low	No	Yes	Low	< 100s	Low	Bit coin	[23][24][25]
PoS	Public	Power full	High	Yes	Yes	High	> 100s	Low	PeerCoin	[26][27]
DPoS	Public	Power full	High	Yes	Yes	High	>100s	-	-	[26][28]
PoA	Public	Power full	High	Yes	Yes	High	>100s	-	Coin Proz	[29][30][31]
PoL	Federated	Power full	High	Yes	Yes	High	> 10s	-	Hayek Coin	[32][33][34]
PBTE	Public	Weak	High	Yes	No	High	> 100s	Semi-trusted	Slim Coin	[31][35][36]

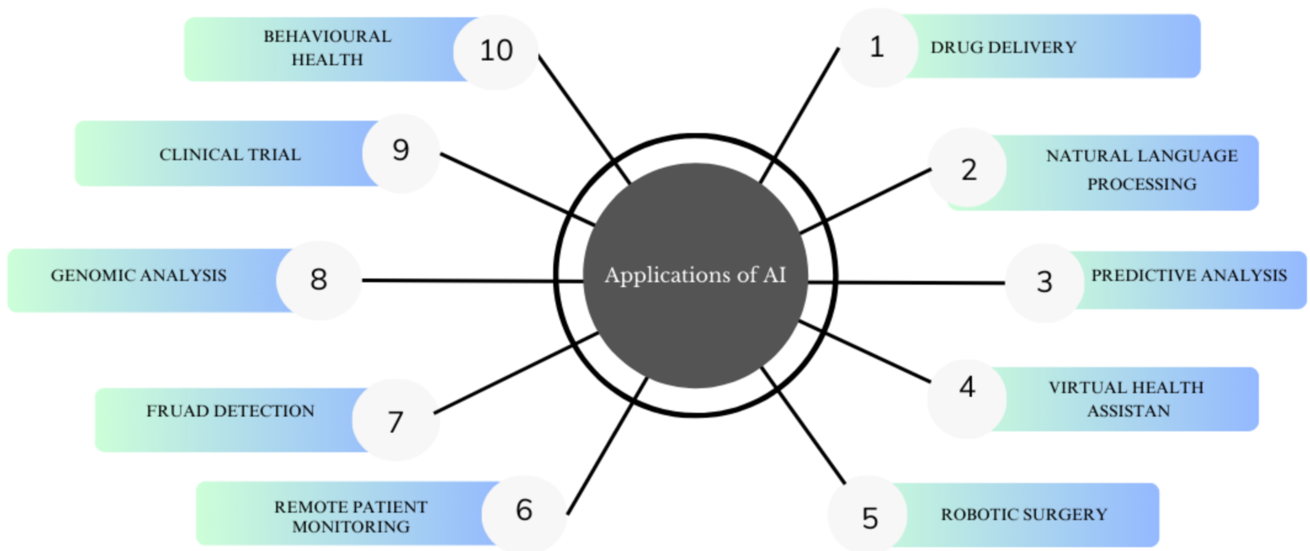

Figure 5. Applications of AI in Healthcare

learning. In 2023, the number of articles published in the fields of ML and DL were 471 and 348 respectively, making them the most prominent areas of research.

A. Blockchain-based ML Techniques for Healthcare

The amalgamation of ML and blockchain exhibits substantial potential in propelling the progress of public health endeavors. Machine learning algorithms provide the ability to extract valuable insights from extensive datasets, hence augmenting the efficacy and precision of healthcare procedures. When integrated with blockchain, these technologies establish a robust and transparent framework for the management of health-related information. Machine learning (ML)–enabled blockchain systems have the potential to make significant contributions to various areas, including real-time illness surveillance, personalized medicine, and the secure interchange of health data. Decentralized machine learning models enable the training of models on dispersed datasets while upholding data privacy, hence fostering collaborative research and analysis. In healthcare, various ML algorithms are employed to analyze and interpret medical information, improve diagnostics, personalize treatment plans, and enhance overall healthcare outcomes.

TABLE VI. Present state-of-the-art for Blockchain-enabled ML and DL

Ref	Application	Security	Dataset	ML / DL Technique used	BC Type	Blockchain Platform	Contribution
[39]	Classification of patients with liver disease or not	Maintaing the privacy of data while data sharing	public liver patient dataset 20 K train data and 1 K test data (Kaggle)	Naïve Bayes, J48, and Random Forest	Public	Ethereum (Smart Contracts)	Proposed a model for early diagnosis of liver disease and demonstrated a remarkable accuracy of 99.9%, surpassing the performance of Naïve Bayes and J48, which achieved accuracies of 99.2% and 89.2%, respectively.
[40]	To classify wearable devices as malicious or non-malicious.	securely storing patient's wearable data	WUSTL EHMS 2020 dataset	Long Short Term Model (LSTM)	Public	Remix IDE	Proposed an AI-based secure and trusted framework.
[41]	Developed a conceptual framework for the early detection and classification of monkeypox	Implement the Role-based access control mechanism to ensure the security	monkeypox dataset of 1905 images	Transfer learning and CNN	Public	Remix IDE	secured blockchain-enabled framework for the early detection of monkeypox.
[42]	Proposes a system architecture for detecting fraudulent transactions and attacks	Detecting and preventing fraudulent data insertion	2 dataset, patient vital data and Ethereum Fraud Detection dataset (Kaggle)	Logistic Regression, Decision Tree, KNN, Naïve Bayes, SVM, and Random Forest	Public	Ethereum (Smart Contracts)	Proposes a system architecture for detecting fraudulent transactions and attacks.
[43]	Real time analysis of large-scale healthcare data, diagnosis, treatment recommendations, and disease prediction.	Only authorized entities can access and modify sensitive health information	100 number of blocks + PHR	LSTM and SVM	Private	Not Mentioned	Developed a blockchain-powered Healthcare systems that enhanced scalability, improved security and interoperability.

TABLE VI. Continue

Ref	Application	Security	Dataset	ML / DL Technique used	BC Type	Blockchain Platform	Contribution
[44]	Detect the breast cance	provide a secure and consistent data-sharing	Wisconsin Breast Cancer Dataset (Kaggle)	RNNs	Private	Not Mentioned	Proposed an IOMT-blockchain based to detect the breast cancer. and used a standard medical dataset.
[45]	Support breast cancer diagnosis	only trusted and reputed agents participate in the decision-making process.	Wisconsin diagnostic breast cancer dataset	fuzzy logic approach	Not Mentioned	Not Mentioned	Presents an architecture that integrates multi-agent learning system and blockchain. Takes a high computational time for reasoning and block creation process.
[46]	A smart blockchain and AI-enabled system is presented for the healthcare sector that helps to combat the coronavirus pandemic.	Not secure	Data is collected in medical images (Chest X-rays) from various clinical labs and hospitals.	Convolutional Neural Network (CNN)	Not Mentioned	Not Mentioned	A new deep learning-based architecture is designed to identify the virus in radiological images.
[47]	Proposes a deep learning algorithm for COVID-19 detection-based X-ray images	Security is maintained with blockchain	Collects the X-ray images from different Datasets	Convolutional Neural Network (CNN) mode	Private	Ethereum	Proposed a smart unsupervised medical clinic without medical staff interventions.
[48]	A hybrid technology to prevent Covid	Not secure	Data is collected from hospitals and other healthcare facilities, both public and private.	Not Mentioned	Not Mentioned	Not Mentioned	Systems comprises the detection of masks, people, and temperatures, as well as the monitoring of information.
[49]	Classification model for lung cancer	Not secure	Survey Lung Cancer	CNN and XGBoost	Not Applicable	Not Applicable	DeepXplainer a new interpretable hybrid DL-based technique for detecting lung cancer and providing explanations of the predictions.

TABLE VI. Continue

Ref	Application	Security	Dataset	ML / DL Technique used	BC Type	Blockchain Platform	Contribution
[50]	Detection of myopia	Data transfer and sharing between collaborators for medical studies	Retinal photographs from Singapore, China, Taiwan, and India.	A new model developed to detect myopia.	Private	Hyperledger.	Detecting internal diseases such as Myopia.
[51]	Identify feature-extracted data from the existing data.	EHRs have a centralized database that is a major security issue	Greater Noida COVID-19 dataset	DNN	token-based approach is used.	Ethereum	The bulk data are reduced to data size which can simply be predictive analysis commentary.
[52]	Detect intrusion in HS network	secure data transmission of IoT-enabled healthcare data	Two public data sources (CICIDS-2017 and ToN-IoT)	Deep Sparse AutoEncoder (DSAE) with Bidirectional Long Short-Term Memory (BiLSTM)	Private	Ethereum smart contract	Blockchain-orchestrated Deep learning approach for Secure Data Transmission in IoT-enabled healthcare system.

1) Artificial Neural Network (ANN)

This relies on the structure and functionality of biological neural networks found in the human brain. ANNs are a crucial element of ML and DL. Researchers used BCT in the context of training neural networks specifically to enhance the optimization of weight configurations for training purposes [54]. The feasibility of such operations has been demonstrated by extensive computations. Furthermore, a neural network-blockchain-based model [55] is observed in the validation process of Personal Health Records (PHR).

2) Naive Bayes

This approach assumes that each feature utilized for categorization does not influence the remaining features. Researchers[56] highlight the successful application of this algorithmic approach in establishing decentralized and collaborative artificial intelligence on blockchain. The process of implementation comprises the creation of a comprehensive dataset and the ongoing dissemination of updated models over a publicly accessible blockchain network, assisted by the utilization of smart contracts. The suggested study improved the effectiveness and reliability of smart contracts by the utilization of an auto-generated smart contract that was specifically tailored for the Ethereum platform [57]. Similarly, in another study[58], authors conducted an inquiry where they trained naive Bayes and random forest classifiers using a dataset that included records of individuals with coronary heart disease, diabetes, and breast cancer. The models were fine-tuned particularly to distinguish between these scenarios, employing the confusion matrix as the evaluative metric.

3) KNN (k-NEAREST NEIGHBOURS)

This is widely utilized in the domain of ML for classification and regression. The algorithm under consideration is non-parametric and instance-based in nature, implying that it does not make any assumptions regarding the underlying distribution of the data. Instead, it relies solely on the data instances themselves to generate predictions. Through the integration of the genetic algorithm with the KNN algorithm [59], a process of attribute pruning based on relevance can be executed.

4) Random Forest

The Random Forest method, known for its versatility in ensemble learning, holds significant importance across multiple disciplines, mainly in the field of healthcare. The primary advantage is to generate numerous decision trees. Every tree is built using various subsets of the available data and features. This strategy effectively addresses the issue of overfitting and improves the overall resilience of the model. Random Forest demonstrates exceptional performance in healthcare applications, specifically in the domains of disease prediction, patient risk assessment, and treatment result prediction.

5) Support Vector Machine (SVM)

This is a highly effective technique in supervised machine learning that is extensively utilized for both classification and regression tasks. The fundamental principle of

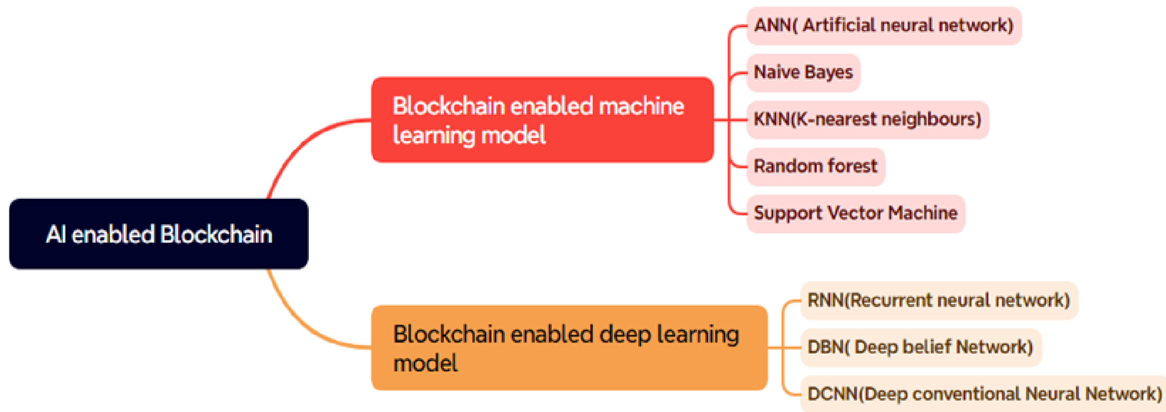

Figure 6. AI-enabled blockchain techniques

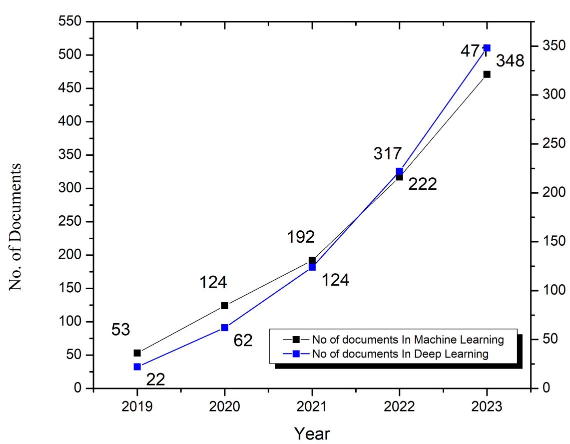

Figure 7. Annual publication in machine learning and deep learning

SVM is to find the optimal hyperplane that can efficiently separate data points belonging to different classes, aiming to maximize the margin between these classes. SVM exhibits remarkable efficiency in high-dimensional areas and is renowned for its adeptness in managing complex datasets. The approach can handle both linear and non-linear interactions by employing various kernel functions, including polynomial and radial basis function kernels.

B. *Blockchain-based DL Techniques for Healthcare*

DL is a subfield of machine learning, that encompasses the utilization of neural networks that consist of numerous layers. This architectural design facilitates the acquisition of sophisticated patterns and representations from extensive and intricate information [60]. When combined with blockchain technology, these aforementioned technologies establish a robust and transparent framework for the effective management of health-related information. The amalgamation of DL with BCT has the potential to improve multiple facets of public health, such as illness surveillance, personalized medicine, and secure data interchange. The collaborative training of decentralized deep learning models enables the effective analysis of varied health datasets while maintaining data privacy, as it involves the utilization of a network of nodes. By enhancing the precision of predictive models, it can facilitate better-informed decision-making. Additionally, it guarantees the security and confidentiality of health data in a decentralized and tamper-proof manner. Various deep learning models employed in the healthcare domain are discussed below:

1) *Recurrent neural networks (RNNs)*

RNNs are well-known for their capacity to preserve input information, which is particularly beneficial in situations that involve sequential data. Researchers [61] dentified and discussed the various obstacles encountered by institutions in the maintenance of electronic health records (EHRs). The authors specifically highlighted concerns related to organizational trust and the susceptibility of EHRs to cyber threats. In order to mitigate these problems, the study suggests the use of a storage system that combines blockchain and Hyperledger technology. This approach aims to improve the security and privacy of medical data. This approach guarantees that patient medical records remain inaccessible unless proper authorization is granted. One alternative approach [62] entails the integration of recurrent neural networks (RNNs) and graph neural networks (GNNs) to forecast forthcoming prescriptions. Recurrent Neural Networks (RNNs) are utilized to observe the continuous sequence of prescriptions, whilst Graph Neural Networks (GNNs) are employed to monitor medical events. By utilizing pre-existing electronic health records, this methodology produces precise forecasts for forthcoming prescriptions.

2) Deep Belief Network (DBN)

This is a highly effective category of artificial neural networks that have been specifically developed for unsupervised learning and feature extraction. Deep Belief Networks (DBNs) are highly effective at collecting hierarchical representations of complex data due to their composition of numerous layers of latent variables connected through Restricted Boltzmann Machines (RBMs). The network undertakes a two-step training procedure, commencing with unsupervised pretraining of each Restricted Boltzmann Machine (RBM) layer to acquire probabilistic representations of the input data. Following this, the complete network undergoes fine-tuning through the utilization of supervised learning methods, which facilitates the extraction of complex features and patterns from the unprocessed input.

Dynamic Bayesian Networks (DBNs) are especially advantageous in situations when the process of manually constructing features is difficult. This is seen in their effectiveness in several tasks, including reducing the dimensionality of data, recognizing images, and processing natural language. The inherent probabilistic characteristics of Dynamic Bayesian Networks (DBNs) enable them to effectively capture and represent uncertainties and interdependencies present in the data. This attribute significantly enhances their adaptability and applicability in various domains within the fields of machine learning and artificial intelligence. The authors in [63] examine the recent advancements made by Dynamic Bayesian Networks (DBNs) in the field of electroencephalography. A theoretical model of a Deep Belief Network is illustrated in Fig.8.

3) Deep Convolutional Neural Network (DCNN)

CNNs are a specialized type of ANN that has been specifically developed for tasks that pertain to visual data, such as image recognition and computer vision. In contrast to conventional neural networks, convolutional neural networks (CNNs) integrate convolutional layers that possess the ability to autonomously and flexibly acquire hierarchical representations of features directly from the unprocessed input data. Convolutional operations and pooling layers are employed in these networks to effectively capture spatial hierarchies of features. The utilization of convolutional layers in the network facilitates the identification of localized patterns, such as edges and textures. Conversely, the pooling layers serve to diminish the spatial dimensions of the data, while still retaining crucial information. Deep convolutional neural networks (CNNs) are composed of numerous convolutional and fully linked layers, enabling them to acquire intricate hierarchical representations of visual characteristics. Convincing evidence has been provided to demonstrate the significant achievements of these models in diverse domains such as picture classification, object identification, and facial recognition. This substantiates their efficacy in extracting and comprehending complex patterns from visual data.

Researchers in [64] investigated the utilization of a CNN model, specifically based on the VGG16 architecture, to detect pneumonia in digitized X-ray images. The proposed research was to accurately identify the existence and extent of pneumonia within these scans. The COVID-19 pandemic has exerted a substantial global influence on communities across the globe. In another study, authors [65] provide a demonstration of a CNN model that utilizes transfer learning. The model is specifically built to accurately detect lung scans that are affected by COVID-19, separating them from scans displaying viral pneumonia and those that are considered normal. The model was trained using a dataset that is publicly accessible. Subsequently, it was evaluated using various metrics, including accuracy, specificity, and F1 value. The suggested framework demonstrated a notable general precision of 92.93%. The aforementioned model has demonstrated its efficacy as a valuable instrument in computer vision applications. Fig. 9 presents a graphical depiction of the foundational architecture of a DCNN. This architecture has a single input and output layer, with two intermediate layers that perform convolutional operations and pooling.

7. Integration of AI With Blockchain

The combination of Blockchain and AI has made notable contributions to the healthcare sector, yet both technologies face challenges when implemented separately[66][67] The advent of decentralized artificial intelligence (AI) has effectively mitigated many constraints. The authors in a previous study had examined the incorporation of blockchain with AI in the field of cardiovascular health [68]. The study emphasized the potential uses of decentralized blockchain platforms to improve data security and facilitate AI computing in data analytics [69]. There are several noteworthy applications of AI with blockchain technology.

1) Electronic health records (EHRs)

EHRs refer to the comprehensive electronic information gathered over time throughout regular healthcare provision. The maintenance of electronic health records offers various possibilities for enhancing patient care, optimizing the performance of clinical trials, and improving the detection of diseases within populations. The protection of EHRs is of utmost importance to prevent unauthorized access and maintain the privacy of individuals' personal information, as it may contain personally identifiable information (PII)[70]. Many electronic health record systems have many difficulties with security, integrity, privacy, and management [71]. The resolution of these concerns is effectively tackled by the incorporation of blockchain technology, as exemplified by the architecture[72] which employs smart contracts on the Ethereum blockchain. Similarly, researchers developed a tamper-proof system called Bheem. The primary objective of Bheem is to guarantee the security and availability of EHRs for patients, health professionals, and external entities [73]. The utilization of blockchain technology in EHRs plays a substantial role in resolving the challenge of interoperability [74]. In many cases, the longitudinal

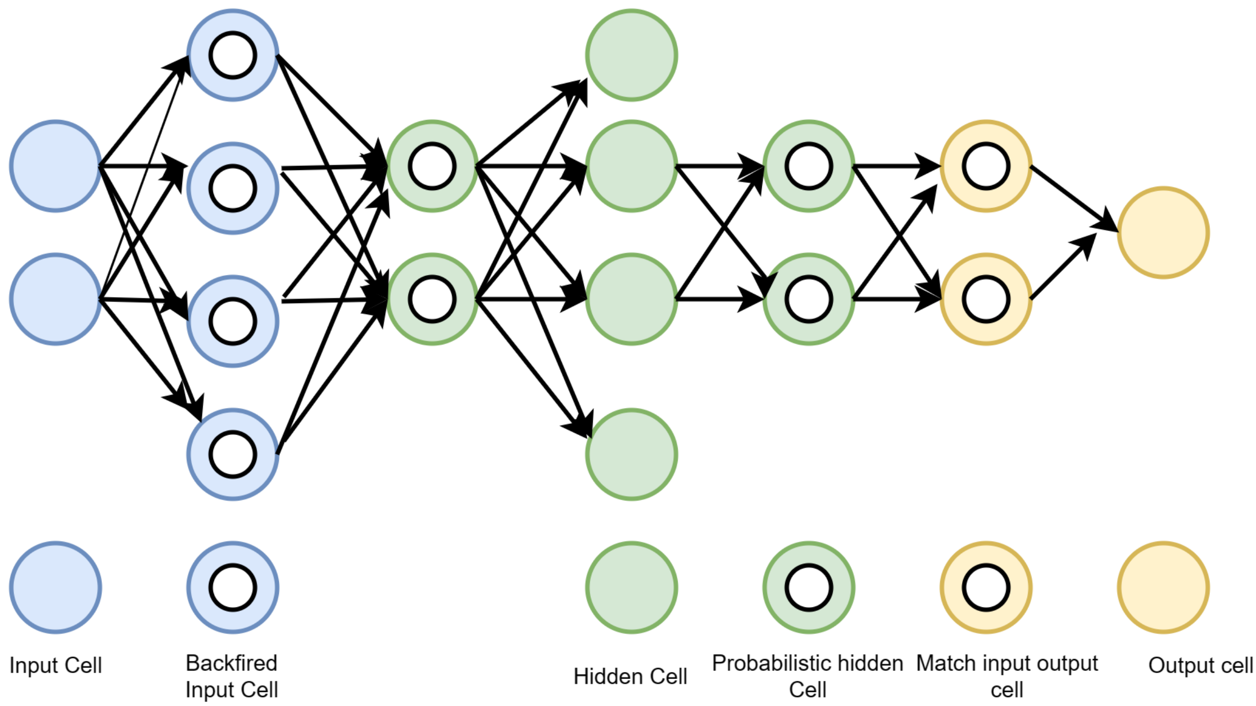

Figure 8. Deep Belief Network Model

data of patients is distributed around several institutions, hence requiring the establishment of a centralized and secure system that multiple healthcare professionals can access. This system serves to address the aforementioned difficulty. The authors presented a concept that combines blockchain and cloud technologies, along with a machine-learning data-quality assessment module, to facilitate the sharing of medical data [10]. An AI-based EHRs system has demonstrated significant advantages, particularly in the augmentation of conventional Early Warning Systems (EWS) that are developed for the prediction of acute severe illnesses. The utilization of data obtained from EHRs is crucial in enhancing the precision and efficacy of these prognostications [75]. Furthermore, the utilization of ML and Natural Language Processing (NLP) techniques has been observed in the context of EHRs to extract quantitative data from a variety of tests, which are then represented in the form of visual synopses [76][77].

2) Drug Delivery and Pharmaceutics

In the past decade, the field of medication delivery has experienced significant progress, particularly with the development of implantable microchips that enable precise control over drug release [78]. Such technologies aspire to enhance efficiency and minimize adverse impacts. The integration AI and ANNs can lead to improvements in the performance of these systems. AI platforms possess the ability to examine biological data, identify prospective targets for medication administration, and investigate various pharmaceutical choices, therefore improving the whole drug delivery procedure [79].

In addition to employing machine learning for precise and effective medication delivery, pharmaceutical organizations have the opportunity to utilize blockchain technology for supply chain management and ensuring drug safety. The authors designed a model [56] consisting of two parts: an ML that utilizes Light GBM and N-gram models to provide precise drug recommendations to customers, and BC enabled supply chain management system that ensures constant tracking and observing of the drug delivery process. Similarly, in another study researchers [80] developed a system that gives priority to the secure management of the drug supply chain [81]. Hyperledger is a highly suggested approach for tackling the problem of counterfeit medications in the pharmaceutical business [82]. Hyperledger Fabric is a private blockchain framework, part of the Linux Foundation's Hyperledger project. With privacy features like channels, secure Docker containers and private data collections, Fabric supports confidential transactions.

3) Clinical Trials Management

The management of clinical trials plays a crucial role in the global development and validation of drugs. The method encompasses two essential stages: patient selection and monitoring. To engage in participation, patients must satisfy criteria related to eligibility, appropriateness, motivation, and empowerment. Nevertheless, the eligibility for testing may be influenced by the patient's medical history, and it is possible that patients who are deemed acceptable for

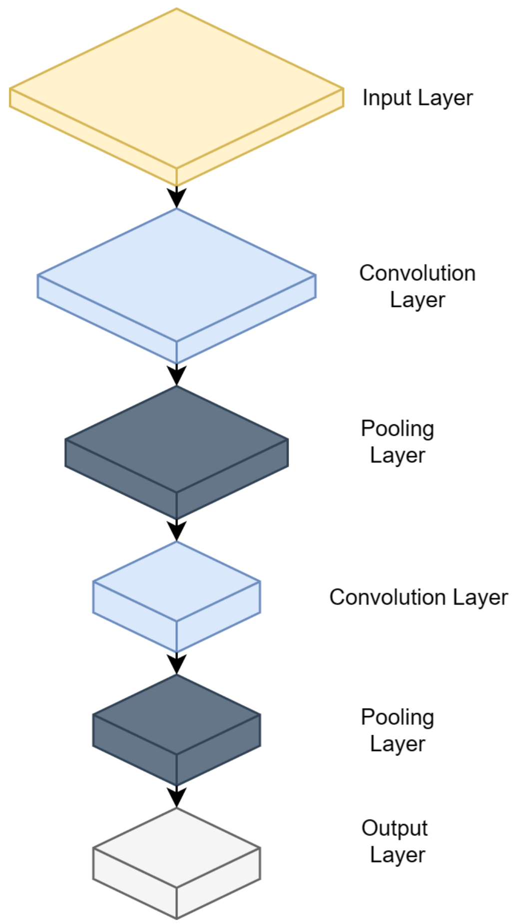

Figure 9. Deep Convolutional Neural Network graphical representation

testing may not necessarily match the drug's intended sub-phenotype or illness stage. The utilization of blockchain technology offers a reliable and distributed means of storing patient medical data [83]. The utilization of unsupervised machine learning techniques allows for the discovery of patterns within clinical data, hence facilitating the identification of patient phenotypes that may derive particular benefits from specific medicines or interventions. The inclusion of unstructured data is crucial in the establishment of comprehensive cohorts [84]. The utilization of advanced deep learning algorithms such as NLP and Optical Character Recognition (OCR) facilitates the process of identifying certain groups of patients. AI and ML technologies can accurately forecast the likelihood of a patient discontinuing treatment or identify the early signs of behavior indicating possible problems in a systematic manner [85]. The feasibility of employing multiagent reinforcement learning to automate blockchain chores in trial management has been demonstrated [86].

4) Disease Diagnosis

Deep learning involves using numerous layers of processing to create a highly abstract representation. It has progressed to the point that researchers regularly utilize them to identify different diseases. The study evaluated a CNN method for predicting the probability of diabetic retinopathy [87]. The researchers included a Batch Normalization (BN) layer into the traditional LeNet model, resulting in the transformation of the CNN model into a novel BNCNN model. The proposed methodology exhibited a training accuracy of 99.85% and a testing accuracy of 97.56%, respectively. The BNCNN model successfully reduced the problem of gradient diffusion, resulting in improved training time and efficiency of the network. Furthermore, the Model-Based Reasoning (MBR) approach, which utilizes EMR and NLP to diagnose illnesses, has reached a remarkable accuracy rate of 95.86 percent.

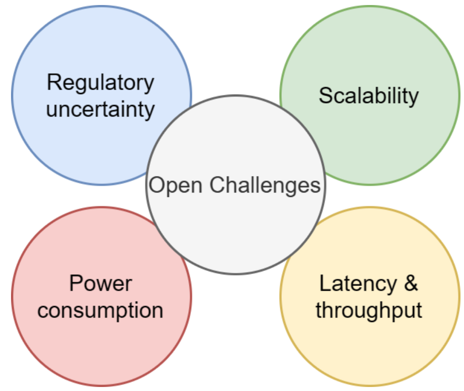

Figure 10. Open challenges

8. Open Research Challenges and Possible Solutions

The incorporation of blockchain with AI in the healthcare industry has resulted in significant transformative advancements across various domains. Nevertheless, these advancements are accompanied by corresponding challenges. The use of novel technologies requires significant financial resources for operations, demonstrates restricted adaptability, and entails large on-site data storage. The absence of a mediator in certain circumstances presents difficulties in effectively resolving legal risks associated with blockchain technology. Fig. 10 provides a comprehensive depiction of the current obstacles encountered by artificial intelligence (AI) enabled blockchain systems within the domain of healthcare. Table VII presents all the open research challenges with their possible solution.

1) Regulatory uncertainty

Regulatory uncertainty surrounding Blockchain technology is a significant challenge that affects its adoption and development. The dynamic and evolving nature of Blockchain combined with its potential to disrupt traditional industries and financial systems. In several nations, blockchain use is governed by various rules and regulations that frequently fall within the technology. Governments are realizing the need to provide clear guidelines to address privacy, security, and compliance concerns. By establishing regulatory sandboxes, collaborating with industry experts,

TABLE VII. Challenges with causes and solutions

Issues	Causes	Solutions
Regulatory uncertainty	• Lack of clarity on compliance. • Regulations on blockchain vary from country to country	Ensuring privacy and security of the stored healthcare data by incorporating compliances such as HIPPA, GDPA
Scalability	• Block size and block creation time. • Inefficient consensus protocol. • Higher confirmation times for block creation and high volume of data. • Number of nodes and transactions	• Sharding technique. • Alternative is proof-of-work. • Redesigning the blockchain. • Storage optimization.
Latency	• Due to use of different consensus protocols	• Hyperledger Fabric
Throughput	• Due to high block size and transactions	• Sharding technique. • Layer-two protocol
Power consumption	• High volume of data. • Large number of nodes and transaction. • Large block size	• Sharding, off-chain transactions, and layer-two scaling
Interoperability	• Different consensus models, transaction mechanisms, and smart contract functionalities	• Using existing standards in blockchain networks, e.g., IBM and Microsoft are employing GS1 based data standard

and fostering open dialogue, regulators can develop robust frameworks that balance innovation with consumer protection and foster Blockchain adoption.

2) Scalability

It is a significant challenge in Blockchain technology, particularly for public or permissionless Blockchains. As the number of nodes participating in a Blockchain network increases, the consensus process and communication between nodes become more complex. Achieving consensus across a large network requires additional time and computational resources, which can slow down transaction processing and decrease scalability. Forks and sharding techniques help to address the scalability issue [88]. This is the method of dividing a Blockchain into multiple "shards." Forking refers to creating a new version of a Blockchain protocol, essentially a divergence from the original Blockchain. This happens when a group of participants in the network disagrees with a particular change or update to the Blockchain protocol. The group can fork the Blockchain and create a new version incorporating their desired changes. This results in two separate Blockchain with different rules, which can operate independently. Forking can help increase the transaction capacity of the Blockchain, as each forked chain has its capacity to process transactions. There are several parts to the process itself, such as the horizontal segmentation of databases, which assigns each network its function or goal. One Blockchain may hold information about a specific coin, while another might be used for system administration. Blockchain is not able to store large transactions in a block. Therefore, scalability is a big challenge for Blockchain-based IoT systems. Sharding divides a Blockchain network into smaller, more manageable parts called shards. Each shard contains a subset of the total network, and each is responsible for processing a portion of the transactions. It can significantly increase the transaction throughput of the Blockchain, as each shard can process transactions in parallel, which reduces the overall load on the network [89][90].

3) Latency

Latency refers to the delay between initiating a transaction and its final confirmation on the Blockchain; refer to (7). Traditional Blockchains often suffer from latency issues due to their consensus mechanisms and block confirmation times. This inhibits real-time transaction processing, limiting Blockchain's applicability in time-sensitive use cases [90].

$$Latency(s) = Confirmationtime - Initiatingtime \quad (7)$$

Latency may be reduced by implementing the Blockchain over a hyperledger fabric framework. In [91], authors compare the Ethereum and hyperledger fabric regarding block creation time and latency. Ethereum takes 12s to create a block for 100 transactions, while hyperledger fabric creates a block within 6s. Ethereum has higher latency as compared to hyperledger fabric.

4) Throughput

Blockchain networks face constraints in terms of throughput, which refers to the number of transactions a network can process within a given time frame as in (8). Ta and Tb are two time periods Blockchain takes for the number of transactions (tx). As transaction volumes increase, traditional Blockchain networks experience congestion, resulting in slower transaction processing and higher fees [90].

$$Throughput(tps) = (count(txfrom(T^a, T^b)))/(T^b - T^a) \quad (8)$$

The throughput of the Blockchain may increase by using the sharding technique and Layer-two protocols built on top of the main Blockchain, providing additional layers for transaction processing. These protocols employ transaction batching and parallel processing techniques to increase the number of transactions processed simultaneously. In the [92] study, hyperledger fabric outperforms the Ethereum framework in terms of throughput whenever the transaction count was raised from 100 to 1000.

5) Power Consumption

Blockchain size is growing in sync with Blockchain's rising popularity. Miners consequently require additional energy and storage capacity for the mining operation. The high energy consumption of some Blockchain networks, however, poses a significant obstacle to their widespread implementation. A lot of well-known Blockchain networks, including Bitcoin and Ethereum, rely on the proof-of-work (PoW) consensus process, which uses a lot of computational resources and energy. The mining procedure, in which participants compete to solve challenging mathematical puzzles, uses a large amount of electricity. The sustainability and environmental impact of Blockchain technology have come under investigation because of high energy consumption. Proof-of-stake (PoS) and proof-of-authority (PoA) are two additional consensus techniques that blockchain networks are investigating to overcome the problem of energy usage. To validate transactions using these procedures, participants must either have a particular quantity of cryptocurrency or be in a trusted position. PoS and PoA drastically lower the energy footprint of Blockchain networks by doing away with labor-intensive mining procedures. Sharding, off-chain transactions, and layer-two scaling solutions are some of the strategies being investigated by researchers and developers to increase the scalability and lower the energy consumption of Blockchain systems [90]. Higher transaction throughput is made possible by these optimizations, which also reduce energy consumption.

9. Discussion and Findings

In the healthcare sector, the convergence of artificial intelligence (AI) and blockchain technology has spurred the development of several primary techniques aimed at revolutionizing various aspects of healthcare delivery and management. One prominent technique is the secure sharing and management of patient data. Blockchain ensures the integrity and privacy of medical records, while AI algorithms facilitate the efficient analysis and interpretation of this data for diagnosis, treatment planning, and research purposes. Another key technique is the enhancement of healthcare supply chain management. By leveraging blockchain's transparency and traceability features, coupled with AI-driven analytics, stakeholders can track the movement of pharmaceuticals and medical devices throughout the supply chain, thereby reducing counterfeit products, optimizing inventory management, and ensuring the authenticity of medications. Additionally, AI-powered blockchain solutions are increasingly being employed for clinical trials management. These technologies enable the secure recording and sharing of trial data among participants while ensuring data integrity and transparency. Furthermore, AI and blockchain are reshaping healthcare payments and billing processes. Blockchain ensures secure and transparent transactions, while AI algorithms aid in fraud detection, reimbursement trend prediction, and billing optimization, leading to more efficient and cost-effective healthcare financial operations. Lastly, the integration of AI and blockchain is facilitating the authentication and traceability of pharmaceuticals.

AI with blockchain technology presents several key challenges in research. One primary issue is the scalability issue inherent in blockchain networks. While AI algorithms require substantial computational resources to process data efficiently, blockchain systems often struggle to handle the computational demands of AI algorithms due to their distributed nature and consensus mechanisms. This can result in performance throughput and latency issues, hindering the real-time execution of AI tasks on the blockchain. Additionally, interoperability remains a significant challenge in merging AI with blockchain technology. AI algorithms typically operate on centralized data sources, whereas blockchain platforms rely on decentralized data storage and consensus protocols. Fig. 11 Illustrates the frequency of challenges encountered in the adoption of blockchain and AI in healthcare based on the published articles.

Regulatory compliance and legal frameworks present hurdles to the adoption of AI-driven blockchain solutions. Researchers are collaborating with policymakers and industry stakeholders to develop regulatory frameworks and guidelines that facilitate the responsible deployment of AI-powered blockchain solutions while ensuring compliance with legal and ethical standards. To address the scalability and power consumption challenge, researchers are exploring techniques such as off-chain computation, sharding, and layer-two solutions to improve the scalability of blockchain

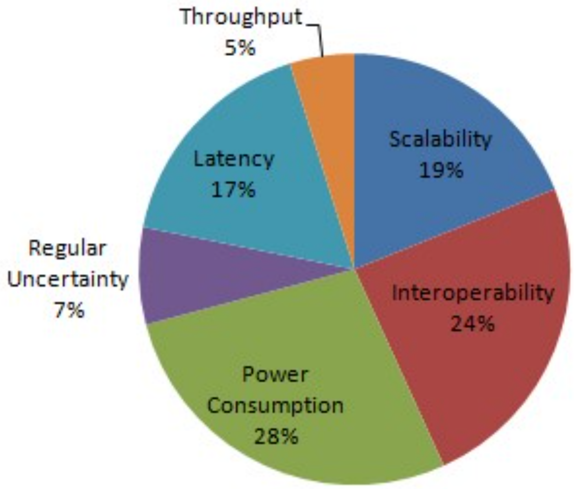

Figure 11. Frequency of challenges encountered

networks and accommodate the computational requirements of AI algorithms. Interoperability is another significant challenge arising from the disparate paradigms of AI and blockchain technology. To enable seamless data exchange and collaboration between AI and blockchain systems, researchers are developing interoperability protocols and standards, such as cross-chain communication protocols and data exchange formats, to facilitate the integration of AI with blockchain networks.

Limitation of this research article is the focused scope on blockchain and artificial intelligence (AI) as supporting technologies. While these technologies hold significant promise for revolutionizing healthcare systems, the exclusion of other emerging technologies, such as Internet of Things (IoT) or big data analytics, may limit the breadth of our analysis. Consequently, our findings and proposed solutions may not fully account for the complex interplay between multiple cutting-edge technologies in healthcare innovation. In order to give an in-depth understanding of the difficulties and potential solutions in healthcare integration, future research should profit from a more complete analysis that takes a wider spectrum of technology improvements into account.

10. Conclusion and Future Scope

Digitization improves the efficiency of computing, storing, and accessing medical records, resulting in enhanced patient treatment experiences. The amalgamation of artificial intelligence with blockchain holds immense promise to transform the healthcare industry by enhancing the privacy of data, connectivity, and decision-making procedures. This paper presents the state-of-the-art on Blockchain-based AI techniques. The article delves into the specific challenges faced in integrating blockchain and supporting technologies into healthcare systems. By identifying and discussing these challenges, the research provides valuable insights into the complexities of implementing blockchain in healthcare and offers a foundation for further exploration and problem-solving. The occurrence rates for achieving scalability, interoperability, and managing power consumption are 19%, 24%, and 28% respectively. In addition to outlining the challenges, the article also explores potential solutions to mitigate these obstacles. This aspect is crucial as it offers practical strategies and recommendations for researchers, practitioners, and policymakers to overcome the identified barriers effectively. Sharding is a more efficient and sustainable solution to the scalability problem, as it allows the network to scale without requiring additional hardware resources. In contrast, forking can result in a fragmentation of the network and can lead to a loss of trust among participants. Forking allows for network upgrades and protocol improvements. Sharding, however, can be difficult to execute as it requires massive modifications to the Blockchain protocol and can potentially result in new security vulnerabilities. To improve transaction performance and power usage, researchers will need to enhance the consensus mechanism in the future. These solutions contribute to advancing the adoption of blockchain technology in healthcare and improving the overall quality and efficiency of healthcare delivery.

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