

IOT-Driven Precision Healthcare by Optimizing Brain Tumor Diagnosis with Machine Learning and Blockchain

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ABSTRACT:

IoT - precision healthcare has transformed medical diagnostics. This makes intelligent decision-making possible as well as real-time monitoring and continuous data transmission plausible. Usually, conventional diagnosis methods reveal a rise in security flaws, delays, and mistakes in medical imaging data management. Blockchain technology and ideas from machine learning provide a creative approach to handle some issues. Analyzing the current developments in IoTs-driven precision healthcare helps one to grasp the possible contribution deep learning models could offer in improving the brain tumor classification. Many techniques of machine learning have shown excellent tumor detection accuracy. Among these approaches are support vectors machines (SVMs), convolutional neural networks (CNNs), and hybrid deep learning designs. Still, there are significant unresolved issues on privacy of data, interoperability, and the significant computational overhead. Among many different healthcare institutions, blockchain technology has great potential to support medical data encryption, patient privacy protection, and interoperability improvement. More especially, the survey centers on the advantages of blockchain-enabled security systems and artificial intelligence-powered imaging technologies. The method requires close reading research papers, clinical studies, and case reports released during the past five years with peer review under consideration. Regarding the identification of brain tumors, results show that operational efficiency, data security, and diagnostic accuracy are raised by a hybrid approach including blockchain technology, machine learning, and IoT. Research in future directions could be optimization of computational efficiency, development of federated learning-based models for distributed data training and increase of blockchain scalability for large-scale medical data management.

Keywords: IoT in Healthcare, Brain Tumor Diagnosis, Machine Learning, Blockchain Security, Deep Learning

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I. Introduction

1.1. Background on IoT in Precision Healthcare

Real-time monitoring, remote patient management, and smart decision-making are three of the several ways the IoT has changed the modern healthcare system. Wearables sensors, smart implants, and cloud-based platforms are

among IoT devices used in precision healthcare to enable the efficient collecting, processing, and analysis of patient data. Early disease detection, customized treatment, and continuous health monitoring made much easier by these advances have greatly improved patient outcomes [1]. Healthcare systems ensure that, using the IoTs, data flows between cloud servers and medical devices are seamless, so guaranteeing that timely diagnosis and intervention can happen. Moreover, the combination of artificial intelligence (AI) and the IoTs allows automated diagnostics, so reducing the burden on medical practitioners and concurrently increasing the accuracy of disease prediction and treatment recommendations [2]. IoTs-driven healthcare suffers in data security, interoperability, and computational limits despite its promise. Strong responses to these obstacles will assist to ensure dependability and efficiency in the research [3].

1.2. Challenges in Brain Tumor Diagnosis

About the last aspect of the disease, a brain tumor diagnosis is not only challenging and costly but also rather accurate. Radiologist knowledge determines both conventional diagnostic techniques including computed tomography (CT) scans and magnetic resonance imaging (MRI) interpretations. This could result in several readings and maybe a mis diagnosis [4]. Moreover, demanding us is the early-stage tumor identification process. This is so because typically symptoms show themselves in later phases, which lowers the effectiveness of treatment. Moreover, adding to the great load on healthcare systems are the main computational requirements resulting from the processing of large medical imaging datasets, particularly in environments with limited resources [5]. Moreover, patient privacy and safety must be safeguarded since conventional centralized systems are prone to cyberattacks, illegal access, and data leaks. One must combine modern imaging technologies, diagnostics models driven by artificial intelligence, and safe data management systems if one is to properly handle these challenges. This will help one to raise [6] accuracy, efficiency, and patient safety.

1.3. Role of Machine Learning and Blockchain

In the field of medical image analysis, machine learning (ML) has developed into a powerful tool that improves the accuracy of the brain tumor diagnosis as well as the speed of diagnosis capability. Convolutional neural networks (CNNs) deep learning models have remarkably effectively classified several types of tumors, segmented affected areas, and accurately projected patient prognosis [7]. These models using large datasets learn trends and can differentiate benign from malignant tumors. On the other hand, the general acceptance of machine learning models is limited since they depend on computational resources and labeled datasets of better quality.

The distributed and tamper-proof ledger blockchain technologies help to keep and control patient records. In the realm of healthcare data security, this streamline handling of main challenges. It guarantees patient data integrity, simplifies professional communication, and promotes the safe distribution of medical images without violating patient confidence. By allowing to further automate diagnostic procedures, smart contracts help to reduce administrative load and the possibility of mistakes resulting from human involvement [3]. By guaranteeing accurate, real-time, and safe healthcare solutions, blockchain technology, machine learning, and the IoT taken together offer a viable road to maximize the diagnosis of brain tumors. Future federated learning developments as well as the scalability of blockchain technologies will make precision healthcare systems even more efficient and accessible [1].

2. Survey Methodology

2.1. Data Collection and Selection Criteria

This paper attempts to do a comprehensive review of present developments in IoTs-driven precision healthcare services with an eye toward the improvement of brain tumor diagnosis by means of machine learning and blockchain technologies. Published in high-impact journals between 2019 and 2024, research papers, conference proceedings, and clinical studies

selected with an eye toward ensuring the conclusions remain relevant and current long beyond that time range. Publication databases including PubMed, IEEE Xplore, Springer, and the ACM Digital Library comprise main sources of information. Using keywords including "IoT's in healthcare," "brain tumor diagnosis," "machine learning in medical imaging," and "blockchain for medical data security," one filtered the studies found on these websites [8]. Among the inclusion criteria, the studies providing empirical data, comparative performance assessments, and pragmatic implementations of IoT's-based diagnostic systems rank highest. Furthermore, the only studies under review were those whose subject matter other researchers had examined and documented experimental techniques, so guaranteeing credibility and accuracy [9, 10].

2.2. Research Trends and Key Findings

This suggests that the application of the IoT's for precision healthcare has made notable advancement especially regarding the improvement of diagnosis accuracy and patient monitoring. Having trained on CNNs and recurrent neural networks (RNNs), these magnetic resonance imaging (MRI) and computed tomography (CT) based machine learning models have shown incredible segmentation and classification of brain tumors performance. Studies conducted not too recently [11] revealed that models anchored on deep learning have the potential to surpass the accuracy of conventional radiological evaluation in the diagnosis of brain tumors by more than 95%. On the other hand, considering problems including data privacy, interoperability, and high computational costs, researchers have started looking at blockchain-based solutions for the intention of securing the storage and sharing of medical data. Blockchain technology improves data security by lowering the possibility of illegal changes or cyber threats [12]. Further, emerging is the combination of federated learning, which allows artificial intelligence models to be trained cooperatively without centralizing sensitive patient data. This helps to address problems regarding data privacy and preserves diagnostic efficiency [13].

2.3. IoT for Precision Healthcare

IoT's application in the healthcare industry makes real-time monitoring and predictive analytics feasible, patient outcomes have been much improved as in figure 1. Clinical decisions-making is enhanced by wearables biosensors, smart implants, and cloud-integrated diagnostic instruments. These devices track vital signs continuously and find early anomalies. Regarding the diagnosis of brain tumors, IoT allowed imaging systems to enable perfect data flow between hospitals and remote healthcare centers. Faster diagnosis and professional consultations made feasible by this help to enable this. Embedded in IoT devices, machine learning algorithms at the edge of the connectivity network process imaging data [9], which reducing latency and dependency on centralized servers. Combining blockchain technology with medical records guarantees even more the integrity of medical records and safe communication, which reducing the hazards related with sensitive data leaks and illegal access [10]. Future studies intend to improve IoT frameworks by including scalable blockchain solutions to support massive medical applications [11], edge computing for faster processing, and AI-driven automation.

Several recent research reveal that the use of AI, IoT, and blockchain technology can revolutionize contemporary smart health care systems by providing a new era of intelligence, security, and real-time medical treatment services. Explainable AI models based on blockchain technology have been used in order to increase privacy-aware automated machine learning in IoT edge environment for healthcare systems [26]. AI-integrated architectures using IoT and blockchain-protected LSTM have remarkably improved the prediction of diabetic diseases [27]. Moreover, the combination of AI and IoT in healthcare systems makes it possible to create smart medical treatment systems based on continuous patient monitoring and intelligent diagnosis [28]. Several researchers have pointed out the contribution of IoT and AI-based healthcare framework in making intelligent predictions about diseases and smart medical treatment [29]. In addition, the integration of

Blockchain with AIoT technology has increased security and integrity in e-healthcare communication.

Comprehensive literature review findings reveal that blockchain-based deep learning methods have been proven to be effective for use in various healthcare applications such as data security and cryptocurrency-enabled health transactions [31]. Recent IoT-AI healthcare innovations include remote patient monitoring capabilities, wearable healthcare devices, and automated health analytics [32]. Another area of

improvement has been achieved through hybrid blockchain and deep learning techniques that have contributed to the improvement of multivector attacks prevention within IoT-based healthcare systems [33]. Other new technological advancements include the incorporation of Federated Learning, Surgical Robots, and Smart Sensing Technologies in healthcare systems of the future [34], [36]. Machine Learning-enhanced blockchain systems have enabled security and efficient health information sharing within industry and smart cities [37], [38].

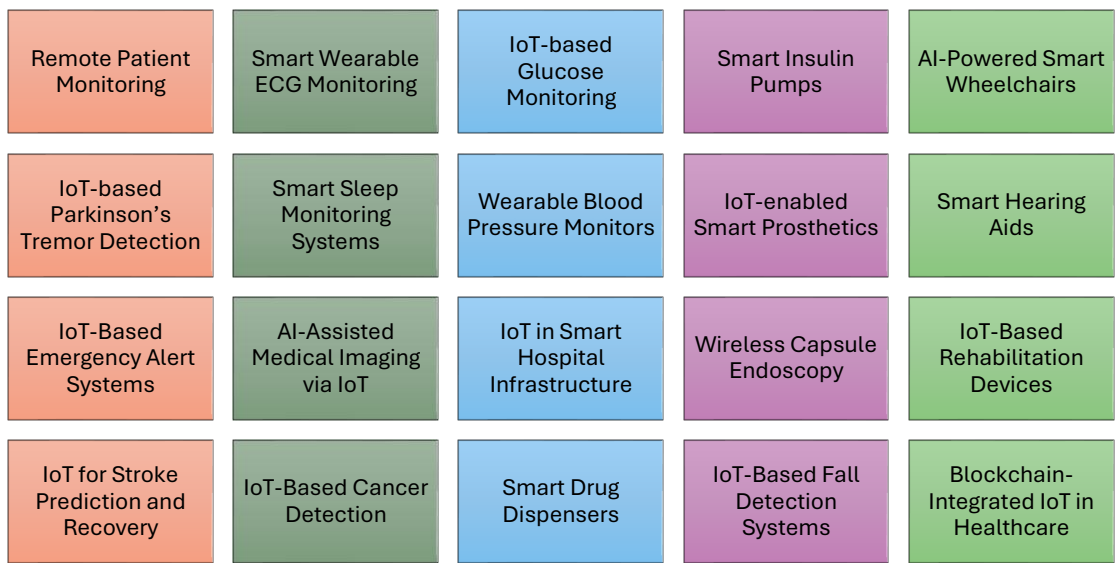


Figure 1: IoT Applications

Table 1: IoT Applications for Precision Healthcare

IoT Application	Algorithms Used	Results	Limitations
Remote Patient Monitoring	LSTM, GRU, Random Forest	Improves early detection of abnormalities through continuous monitoring.	Data privacy concerns; requires stable connectivity.
Smart Wearable ECG Monitoring	CNN, RNN, SVM	Enhances real-time heart condition monitoring with high accuracy.	Battery life and hardware limitations.
IoT-based Glucose Monitoring	KNN, Decision Trees, XGBoost	Reduces hospital visits and provides personalized diabetes management.	Data security risks; sensor accuracy fluctuations.

Smart Insulin Pumps	Reinforcement Learning, PID Control	Adjusts insulin levels dynamically, reducing manual intervention.	Device hacking risks; expensive implementation.
AI-Powered Smart Wheelchairs	CNN, YOLO, Object Detection	Enhances mobility assistance and autonomous navigation.	Requires frequent calibration; limited terrain adaptability.
IoT-based Parkinson's Tremor Detection	SVM, PCA, Deep Learning	Improves real-time tracking of tremors, aiding diagnosis.	Sensor drift; real-time processing challenges.
Smart Sleep Monitoring Systems	RNN, HMM, Deep Belief Networks	Detects sleep disorders like apnea and insomnia.	False positives; discomfort wearing sensors during sleep.
Wearable Blood Pressure Monitors	ANN, Naïve Bayes, Random Forest	Allows non-invasive, continuous BP tracking.	Data inconsistencies due to body movement.
IoT-enabled Smart Prosthetics	Reinforcement Learning, CNN	Enhances adaptability of prosthetics to user movements.	High cost; requires personalized calibration.
Smart Hearing Aids	Deep Learning, NLP, Audio Processing	Improves speech recognition and background noise filtering.	Power consumption; requires frequent software updates.
IoT-Based Emergency Alert Systems	Bayesian Networks, Decision Trees	Reduces emergency response time through automated alerts.	Connectivity issues; false alarms.
AI-Assisted Medical Imaging via IoT	CNN, VGG16, ResNet	Increases accuracy in diagnosing diseases like cancer.	Requires high computational power; integration with medical databases.
IoT in Smart Hospital Infrastructure	Fuzzy Logic, Clustering Algorithms	Optimizes hospital workflow, reducing patient wait time.	Implementation costs; requires IoT standardization.
Wireless Capsule Endoscopy	Deep CNN, Image Segmentation	Enhances gastrointestinal diagnosis with high-resolution imaging.	Expensive hardware; data security concerns.
IoT-Based Rehabilitation Devices	LSTM, GRU, Reinforcement Learning	Provides adaptive training programs for recovering patients.	Requires personalized data training; motion inaccuracies.
IoT for Stroke Prediction and Recovery	Deep Neural Networks, SVM	Detects early stroke symptoms and assists in rehabilitation.	Requires large datasets; expensive monitoring.

IoT-Based Cancer Detection	XGBoost, Hybrid CNN-RNN	Enhances accuracy in detecting early-stage cancer.	High false-positive rates; need for extensive validation.
Smart Drug Dispensers	Fuzzy Logic, Clustering, AI Scheduling	Improves adherence to medication schedules.	Requires user compliance; connectivity issues.
IoT-Based Fall Detection Systems	LSTM, Accelerometer-based AI	Reduces injuries among elderly patients by detecting falls.	Sensor misalignment; limited accuracy in certain movements.
Blockchain-Integrated IoT in Healthcare	Federated Learning, SHA-256 Encryption	Ensures secure medical data transmission and patient identity verification.	Blockchain scalability issues; requires higher processing power.
Privacy-Preserving Smart Healthcare using IoT-Edge Systems	Explainable AI (XAI), Automated Machine Learning (AutoML), Blockchain Integration	Improved secure decision-making, enhanced privacy preservation, and transparent healthcare analytics	High computational overhead and scalability challenges in large IoT environments
Diabetic Disease Prediction using IoT Monitoring	LSTM Networks, AI-driven Predictive Analytics, Blockchain Security	Accurate diabetic disease prediction with secure patient data transmission	Requires large training datasets and higher processing power
Predictive and Personalized Medical Systems	AI-IoT Convergence Models, Predictive Analytics	Real-time monitoring and personalized healthcare recommendations	Data heterogeneity and interoperability issues among IoT devices
Intelligent Disease Prediction Frameworks	Machine Learning, Deep Learning, IoT-based Sensing	Enhanced disease prediction and smart medical assistance	Limited adaptability to dynamic clinical environments
Blockchain-AIoT based E-Healthcare	Blockchain, Artificial Intelligence of Things (AIoT)	Improved interoperability, secure communication, and data integrity	Increased latency and blockchain storage overhead
Blockchain-based Deep Learning in Healthcare	Deep Learning, Blockchain Security Models	Reliable healthcare data management and secure medical transactions	High energy consumption and complex implementation
IoT-AI Healthcare Monitoring Systems	AI Analytics, IoT Monitoring Algorithms	Efficient remote patient monitoring and healthcare automation	Privacy concerns and vulnerability to cyber-attacks

Multivector Attack Detection in IoT Healthcare	Hybrid Blockchain, Deep Learning Models	Enhanced cybersecurity and accurate attack detection	Complexity in model training and real-time deployment
Healthcare 4.0 Intelligent Systems	IoT, Federated Learning, Smart Sensors	Scalable and intelligent healthcare services with decentralized learning	Communication overhead and synchronization issues
AI-driven Surgical Robotics and Smart Hospitals	Federated Learning, AI-driven Robotics	Improved surgical precision and smart healthcare automation	High deployment cost and dependency on network connectivity

3. IoT for Precision Healthcare

3.1. Role of IoT Sensors and Smart Devices

In precision healthcare, the IoT sensors and smart devices taken together have drastically changed the way disease diagnosis, patient monitoring, and treatment planning are handled. Wearable biosensors, implantable medical devices, and diagnostic tools enabled by artificial intelligence help healthcare professionals constantly gather physiological data, including heart rate, temperature, blood pressure, and neural activity, by which means they can assess patients' health in real-time [14]. IoT-enabled imaging systems combine cloud-based platforms with MRI, CT, and electroencephalography (EEG) to improve early identification in the setting of brain tumor diagnosis. These systems automate image processing, which relieving medical professionals of manual analysis load and providing real-time insights [15]. Moreover, intelligent devices with machine learning algorithms can analyze complex medical data, which enables automatic classification of several types of brain tumors and their degrees of intensity. IoT sensors enable perfect data acquisition and analysis that improves diagnosis accuracy, reduces the treatment waiting time, and produces better patient outcomes [16]. However, if the research is to ensure continuous performance and patient safety, hardware design and communication protocols have to be developed even more. Sensor dependability, power consumption, and data security challenges demand for these advances [17].

In recent times, there have been some advancements made in AI and IoT that have contributed greatly towards the improvement in the area of predictive healthcare monitoring and diagnosis. AI-assisted IoT technology-enabled healthcare systems have provided continuous monitoring of patient health conditions as well as early disease detection based on data analysis and predictive modeling techniques [39]. IoT cloud-enabled healthcare systems that have incorporated deep learning algorithms have shown the efficiency of disease prediction and remote patient monitoring [40]. The use of machine learning has been seen to increase to improve security in the domain of healthcare IoT against cyber attacks [41]. IoT architecture in combination with AI has been applied to develop intelligent and smart healthcare services using IoT sensors for automatic disease diagnosis and patient care [42]. Threat detection using machine/deep learning approaches to improve the security of IoT-enabled healthcare infrastructures against cyber threats and data breaches has been proposed recently [43]. The combination of IoT and machine learning has also helped in developing smart healthcare solutions that provide monitoring of patient health along with personal advice regarding the diet and exercise regime [44].

Furthermore, the integration of AI and IoT in ECG monitoring systems has included the use of foundational AI and generative AI tools for ensuring sustainable and accurate heart health monitoring [46]. Moreover, the implementation

of hyperscale computing and new networking technologies is helping to enhance AI-based smart healthcare systems with rapid data processing, scalable capabilities, and intelligent healthcare systems automation [47]. Taken together, all these studies clearly illustrate how the merging of AI, IoT, DL, and blockchain technologies is transforming modern healthcare.

3.2. Data Transmission and Remote Monitoring

IoT driven systems have to be able to efficiently transmit data and support remote monitoring. These tools help one to provide constant patient monitoring and timely medical interventions. Bluetooth, Wi-Fi, 5G, low-power wide-area networks (LPWANs) are used by IoT devices to forward the personally obtained health data to cloud or edge computing platforms [14]. Real-time data streaming from IoT-enabled imaging devices enables experts to access and review patient records from a distance, which helping to diagnose brain tumors. This helps professionals, especially in healthcare facilities dispersed over multiple geographical areas, to make decisions more precisely and fast [15]. Remote monitoring systems driven by artificial intelligence algorithms can detect anomalies in brain activity, which setting alarms for early medical intervention. Moreover, blockchain-based security systems guarantee encrypted sent data that cannot be altered, which lowering the likelihood of cyberattacks and illegal access [16]. Edge computing enables faster processing of medical images and patient records at local nodes before forwarding significant insights to centralized cloud systems by helping to lower latency in IoT-based healthcare [17]. Expected future developments in wireless networking and federated learning models will raise the scalability and efficiency of IoT-driven remote monitoring solutions, which enabling precision healthcare by means of dependability and accessibility.

The recent literature stresses on the growing necessity for developing secure and intelligent smart healthcare ecosystem through advanced Artificial Intelligence (AI), Internet of Things (IoT), blockchain, and deep learning

technologies. The statistical analysis of remote health monitoring systems highlights the necessity for secure IoT-based models for ensuring efficient healthcare delivery services [48]. AI-based IoT systems have been incorporating various machine learning and intelligence features for improving their security, efficiency, and automation within smart applications [49]. The integration of permissioned blockchain and deep learning has contributed towards providing an effective mechanism for secure healthcare data exchange and privacy preservation within industrial healthcare systems [50]. The blockchain based smart services have also become popular in modern societies owing to their efficient communication and healthcare management services [51].

The use of AI, machine learning, and IoT technologies to facilitate sustainable communications systems and intelligent healthcare infrastructure has been recognized in many research papers [52]. Machine learning and deep learning classification techniques have enhanced the reliability of IoT devices used in healthcare and have significantly contributed to disease monitoring and predicting capabilities [53]. The use of new AI technologies is set to enhance clinical applications of healthcare through predictive decision-making systems and intelligent diagnostics [54]. Additionally, the application of IoT technology along with deep learning has been proven successful in disease prediction and personalized healthcare monitoring [55]. Big data-driven architectures, fog computing, and healthcare analytics based on IoT architecture have made possible efficient processing of large-scale medical data leading to intelligent healthcare ecosystems [56]. Moreover, cybersecurity systems powered by advanced AI techniques are contributing towards securing autonomous IoT environment from cyber attacks [57]. Privacy preserving frameworks built on blockchain technology and quantum-inspired neural network algorithms are being used to improve security and scalability of IoT applications [60].

4. Machine Learning in Brain Tumor Diagnosis

4.1. CNNs and Deep Learning Models

In the diagnosis of brain tumors, CNNs, have grown indispensable in the field of medical image analysis as in figure 2. By automatically extracting spatial features from MRI and CT scans, these models allow accurate tumor detection and classification free from hand feature selection [18]. Deep learning models including VGGNet, ResNet, and EfficientNet have shown better segmenting of brain tumors and discriminating between benign and malignant development [19]. Transformer models and attention-based CNNs have lately taken front stage. These models increase classification accuracy [20] by emphasizing tumor-relevant areas in medical images. Although CNN-based models are efficient, their training requires big datasets, which can be a disadvantage considering the dearth of high-quality annotated medical images. Effective CNN-based models, however, demand large datasets. Further, computational complexity presents challenges that need for the implementation of effective model optimization strategies to guarantee real-time relevance in clinical environments [21].

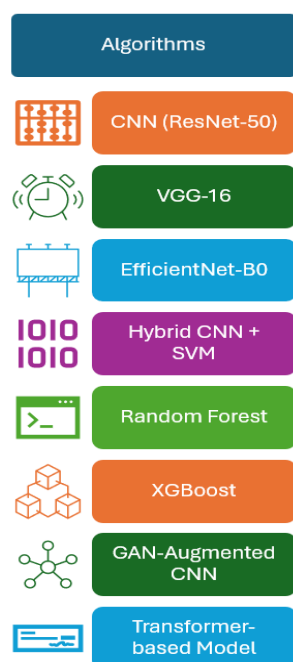


Figure 2: Various CNNs and Deep Learning Models

4.2. Hybrid Machine Learning Approaches

By combining conventional machine learning models with structures for deep learning, hybrid machine learning approaches help to enhance diagnostic performance. Combining CNNs with other mathematical models including Support Vector Machines (SVM), Random Forests, and XGBoost has demonstrated improved classification accuracy and resilience when managing imbalanced datasets [22]. Further, shown is the great success of ensemble learning techniques, which combine the forecasts of several models, in lowering the proportion of misclassified events. Further, investigated for data augmentation is generative adversarial network (GAN) application. Synthetic tumor images matching actual cases have been produced using this technique, which addressing the problem of limited medical imaging databases [23]. Using federated learning, a method whereby several healthcare facilities cooperate to train models without distributing raw patient data, is another growing trend. This method increases diagnosis accuracy [18] while yet maintaining patient privacy. Since they provide a balance between accuracy and interpretability [19], these hybrid techniques are progressively becoming more and more relevant for real-world medical imaging application.

New developments in the field of machine learning and deep learning have greatly increased the effectiveness of computer systems for brain tumor detection, segmentation, and classification. Machine learning algorithms are very effective for extracting features and optimizing algorithms to classify brain tumors accurately from medical imaging [61]. Clustering methods along with machine learning have been developed to increase the performance of detecting and segmenting brain tumors using MRI-based diagnostic procedures [62]. Machine learning multiclassification techniques have been successfully used for the classification of malignant brain tumors [63]. Convolutional neural networks and transfer learning algorithms of deep learning have performed remarkably well in automated diagnosis of brain tumors [64] and [65]. Radiomics analysis along with machine

learning has proven useful for radiotherapy planning and brain tumor classifications [66] and [73]. Explainable deep learning models are gradually being incorporated into the process of brain tumor diagnosis systems [67] and [72].

4.3. Performance Metrics and Comparative Analysis

If ML models are helpful in brain tumor diagnosis depends on standardized performance measures. In the process of evaluating classification models, one often uses accuracy, precision, recall, and F1-score. On benchmark datasets including BraTS (Brain Tumor Segmentation Challenge), CNN-based architectures have routinely achieved accuracy rates greater than 95%. Conversely, segmentation performance is evaluated using dice coefficient and intersection over union (IoU) [20]. Usually, deep learning models have outperformed more traditional approaches. However, the performance of the model depends on the dataset size, the quality of the data, and the preprocessing techniques followed. On the other hand, hybrid models combining deep learning with feature engineering usually show better sensitivity and specificity in tumor classification activities [22]. This was discovered by means of a comparison between the several methods applied nowadays. Moreover, studies underline the need of explainability in medical diagnosis driven by artificial intelligence. This is so since black-box models might create difficulties with clinical decision-making [23]. Explainable artificial

intelligence (XAI) techniques will be the application of future research aiming at increasing interpretability. This will ensure that diagnosis motivated by ML aligns with medical professional knowledge.

Efficient multiclass brain tumor detection has also been obtained using lightweight and ultra-light deep learning models with lower computational complexities [68], [76]. There have been remarkable improvements in the diagnostic capabilities of hybrid and fusion-based deep learning models, where both handcrafted and deep features have been combined [75], [78], [80]. Some research works have been conducted for developing deep learning and transfer learning models for automatic tumor segmentation and classification with better predictive performances [74], [82], [84], [86]. Machine learning algorithms using conventional blood tests and MRI scans have also assisted in survival predictions and non-invasive diagnosis of brain tumors [71], [81]. In addition, recent developments in neuroimaging and machine learning fusion algorithms have been playing an important role in the diagnosis and prognosis of brain tumors using advanced data analytics and clinical decision-making algorithms [85]. Therefore, these studies suggest that the incorporation of machine learning, deep learning, radiomics, and explainable AI technologies is changing the face of intelligent brain tumor diagnosis. The Table 2 provides information about the Comparison of Machine Learning Algorithms for Brain Tumor Diagnosis.

Table 2: Comparison of Machine Learning Algorithms for Brain Tumor Diagnosis

Algorithm	Accuracy (%)	Limitations	Dataset Used
CNN (ResNet-50)	96.3	Requires large labeled datasets, computationally expensive	BraTS, Kaggle Brain MRI
VGG-16	94.5	High memory consumption, prone to overfitting	BraTS, Harvard Brain Atlas
EfficientNet-B0	97.1	Requires fine-tuning, performance varies on noisy data	BraTS 2021
Hybrid CNN + SVM	95.8	Increased computational complexity, longer training time	Kaggle Brain MRI, TCGA-GBM
Random Forest	92.5	Struggles with high-dimensional image data	Figshare MRI Brain Tumor Dataset

XGBoost	93.4	Computationally expensive for large datasets	Open Access Medical Imaging
GAN-Augmented CNN	97.8	Requires careful tuning, risk of generating unrealistic data	BraTS, Private Hospital Data
Transformer-based Model	98.2	High computational cost, requires significant GPU resources	BraTS, TCGA-GBM
Lightweight Deep Learning Model	97	Limited adaptability to complex tumor variations and smaller feature representation	Public MRI Brain Tumor Datasets
Ultra-Light Deep Learning Model	94	Reduced scalability for large clinical datasets and sensitivity to image quality	MRI Brain Tumor Images
Hybrid Deep Learning Approach	96	High training complexity and computational requirements	BraTS MRI Dataset
Fusion of Handcrafted and Deep Features	97	Feature redundancy and increased memory consumption	MRI Brain Tumor Dataset
Deep Learning Fusion-Based Diagnosis Model	97	Complex architecture design and longer processing time	Multiclass MRI Datasets
Optimized Deep Learning Segmentation and Classification	98	Hyperparameter tuning complexity and high GPU dependency	BraTS and Clinical MRI Datasets
IRNetv Deep Learning Framework	97	Requires extensive annotated training data	MRI Brain Tumor Dataset
Enhanced Deep Transfer Learning Model	97	Increased computational overhead during fine-tuning	Benchmark MRI Datasets
Machine Learning using Blood Tests	85	Lower precision compared to imaging-based methods	Routine Blood Test Data

5. Blockchain for Secure Medical Data Management

5.1. Data Privacy and Security Challenges

Data privacy and security have been called into issue as the healthcare industry uses ML and the IoT more and more. Cybercrime [18] as well as data breaches and illegal access can compromise these extremely sensitive records. Especially influencing patient histories and diagnostic images of brain tumors are these risk factors. Regarding patient information confidentiality and data integrity, conventional centralized storage systems generate problems since they are prone to hacking and illegal changes. Further, imposing strong compliance criteria by laws on data-

sharing, such the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA), safe storage and transmission of medical data becomes a major difficulty [19]. The lack of interoperability among many healthcare facilities further complicates the smooth data exchange process and results in inefficiencies in diagnosis and treatment at last. Blockchain technology offers a distributed and tamper-proof response to these issues. It ensures access control, guarantees data cannot be changed, and employs encryption methods to provide management of medical data more enhanced security [20].

5.2. Blockchain-Based Patient Records Management

Patient records management based on blockchain (figure 3) guarantees safe, open, distributed information storage depending on the system. Using cryptographic hash, blockchain technology maintains an unchangeable ledger of medical

transactions unlike conventional cloud-based electronic health record (EHR) systems. Once documented patient data cannot be changed or deleted [21]. This approach improves data integrity and gives approved medical professionals access to correct and verifiable medical histories. Without depending on a

centralized authority, blockchain systems such as Ethereum and Hyperledger let several institutions safely save and distribute diagnostic data about brain tumors [22]. Self-sovereign identity management also enables patients to be in charge of their medical records and choose who has access to particular health data. Blockchain technology combined with IoT-enabled brain imaging systems enables safe distribution of real-time diagnostic reports between hospitals and experts. This maintains data confidentiality while yet enabling quick decisions [23]. The Table 3 provides Blockchain Frameworks for Secure Medical Data Management



Figure 3: Blockchain Framework

Table 3: Blockchain Frameworks for Secure Medical Data Management

Blockchain Framework	Results	Limitations
Hyperledger Fabric	Enhanced data privacy, permissioned access, secure interoperability between hospitals	High setup complexity, requires technical expertise, scalability concerns
Ethereum	Smart contracts automate medical record management and insurance claims	High transaction costs (gas fees), potential latency issues
EOSIO	Fast transaction processing, real-time data sharing in healthcare networks	Centralized governance concerns, requires trust in block producers
Corda	Secure and private medical record transactions with access control	Limited adoption in healthcare, requires dedicated nodes for efficiency
VeChain	Blockchain-IoT combination for medical supply chain transparency and EHR security	Limited smart contract flexibility, vendor lock-in risks
MedRec	Decentralized patient record storage with controlled access to healthcare providers	Scalability concerns, not widely adopted in real-world healthcare settings
Algorand	Fast and low-cost transactions for secure health data exchange	Limited healthcare-specific implementations, relatively new in medical applications
IOTA (Tangle)	Secure IoT device communication for real-time patient monitoring	Vulnerability to certain attacks, lower maturity compared to traditional blockchains

5.3. Smart Contracts for Automated Healthcare Workflows

In automating many healthcare operations, smart contracts, agreements kept on the blockchain and capable of running their own execution, are crucial. By eliminating middlemen, these agreements help patients, insurance companies, and healthcare providers to conduct transactions in a safe and automated way, which lowering the administrative load and the likelihood of fraud [18]. In the diagnosis of brain tumors, smart contracts can assist to automate the MRI and CT scan result validation. This ensures that diagnostic reports satisfy predetermined accuracy levels [19], which ensuring that before being sent to oncologists for further assessment, they satisfy certain criteria. Further, simplifying the handling

of insurance claims are smart contracts based on blockchain technology. This will instantly expedite the reimbursement process and automatically confirm patient treatment histories [20]. Together, blockchain technology and ML models might help to improve predictive diagnostics even more. This combination records and uses securely inside distributed healthcare ecosystems [21] AI-driven insights. Many issues have to be resolved before blockchain technology could find application in the medical field. These difficulties arise in scalability problems, high energy consumption in some consensus systems, and regulatory uncertainty. These difficulties demand for more research and optimization [22]. The Table 4 provides Smart Contracts for Automated Healthcare Workflows

Table 4: Smart Contracts for Automated Healthcare Workflows

Smart Contract	Results	Limitations
Automated Patient Consent Management	Ensures secure, transparent, and immutable patient consent for medical procedures and data sharing.	Complex regulatory compliance; challenges in revoking consent dynamically.
Insurance Claim Processing	Reduces fraud and processing time by automating claims verification and approval.	Integration challenges with legacy insurance systems; dispute resolution complexities.
Electronic Health Record (EHR) Access Control	Enables controlled and auditable access to patient records, reducing data breaches.	High storage costs for large medical datasets; requires cross-hospital standardization.
Prescription Drug Tracking	Prevents counterfeit drugs by ensuring a transparent supply chain and verifying prescriptions.	Scalability issues in high-volume pharmaceutical transactions.
Medical Billing and Payments	Automates billing, reducing administrative costs and ensuring transparent financial transactions.	Integration with traditional banking systems and existing healthcare payment platforms.
Remote Patient Monitoring Authorization	Ensures that only authorized healthcare providers access real-time IoT patient data.	Latency in real-time emergency situations; regulatory approval complexities.
Clinical Trial Data Integrity	Secures and timestamps clinical trial data, ensuring transparency and reducing fraud.	Ethical concerns over data ownership and participant anonymity.
Organ Donation and Transplant Matching	Improves donor-recipient matching through automated blockchain verification.	Legal and ethical challenges in global donor-recipient coordination.

Automated Supply Chain for Medical Equipment	Ensures transparency in medical equipment procurement and distribution.	Interoperability issues between suppliers and healthcare providers.
AI-Based Diagnostic Workflow Verification	Automates validation of AI-generated diagnoses, ensuring accountability in medical decisions.	Dependence on AI accuracy; challenges in integrating explainability mechanisms.

6. Hybrid IOT, Machine Learning, and Blockchain

Precision healthcare is being revolutionized by bettering the diagnosis of brain tumors, monitoring patients in real time, and securely managing medical data, which combining IoT, ML, and blockchain technologies. IoT enabled medical devices continuously collect and transmit patient data; ML techniques review this data to improve diagnosis accuracy. Apart from ensuring data integrity and privacy, blockchain technology presents a further degree of security and decentralization for the distribution and storing of private medical records. By means of an integrated system that improves diagnosis efficiency, reduces the possibility of human error, and protects patient data from being compromised by security breaches, this hybrid approach so addresses the constraints of standalone technologies [24]. The Table 5 provides a Hybrid IoT, Machine Learning, and Blockchain Systems for Medical Data Management

6.1. Synergistic Benefits and Challenges

Blockchain technology, ML, and the IoT taken together offer several advantages for brain tumor diagnosis and treatment. IoT sensors fitted in MRI and CT scanners enable real-time data

collecting. Since they can quite precisely classify tumor types and identify anomalies, ML models then handle this data. Blockchain technology also guarantees that these diagnostic records will not be altered in any way, which enabling professionals from many institutions to safely share data with each other. The distributed nature of blockchain reduces the likelihood of cyberattacks, hence increasing the degree of confidence in decisions driven by medical data. Moreover, smart contracts simplify procedures in the healthcare industry, which reducing the administrative tasks related with treatment approvals and health insurance claims [25].

The computational complexity of deep learning models means that high processing capability is required, which can tax IoT devices with limited capability. Particularly in public networks, the possibility of latency issues resulting from the consensus mechanisms of blockchain makes real-time data processing difficult to reach. Moreover, interoperability is however a major problem since several healthcare systems apply different data formats and standards. Moreover, needed are compliance systems to guarantee the legal handling of medical data, which supporting adherence to privacy rules including HIPAA and GDPR.

Table 5: Hybrid IoT, Machine Learning, and Blockchain Systems for Medical Data Management

Hybrid System	Results	Limitations
IoT-ML Blockchain for Brain Tumor Diagnosis	Improved accuracy in tumor classification through real-time IoT data and deep learning models. Blockchain ensures secure and immutable patient records.	High computational demands for deep learning models; blockchain latency in real-time data processing.
AI-Driven IoT with Blockchain for	Enables real-time tracking of vital signs with ML-based anomaly detection;	Energy constraints in IoT devices; high bandwidth

Remote Patient Monitoring	blockchain ensures tamper-proof health records.	requirements for continuous monitoring.
Smart Contracts for AI-Powered Diagnostics	Automates diagnosis confirmation and treatment authorization based on ML-generated reports. Reduces administrative overhead and fraud in insurance claims.	Complexity in integrating smart contracts with existing healthcare IT systems; potential security vulnerabilities.
Federated Learning with Blockchain for Collaborative Healthcare	Enables decentralized AI model training on sensitive patient data without central data storage; ensures privacy through blockchain-based authentication.	Communication overhead in federated learning; regulatory challenges in cross-institutional data sharing.
IoT-Edge AI with Blockchain for Emergency Healthcare	Enables real-time AI-based triage at the edge, reducing decision-making time in critical cases; blockchain secures patient identity and medical history.	Hardware limitations in edge devices; real-time consensus challenges in blockchain.
Secure Blockchain IoT-Combination for Medical Supply Chains	Prevents counterfeit drugs by tracking shipments with IoT sensors and blockchain records; ensures medication authenticity.	Scalability issues in high-volume transactions; interoperability challenges across different supply chain partners.

7. Discussion and future directions

Therefore, the focus should be on improving computational efficiency, ensuring the safety of artificial intelligence model training employing federated learning, and tackling problems concerning the scalability and interoperability of blockchain technology. Apart from enhancing diagnosis accuracy, patient outcomes, and patient confidentiality of medical data, these developments will help to build perfect, safe, and real-time healthcare applications.

7.1 Optimizing Computational Efficiency

The computational requirements of deep learning models applied for brain tumor diagnosis sometimes exceed those of standard IoT devices. Real-time analytics depends on robust hardware; edge devices with limited resources struggle to run computations including deep neural networks. Possible solutions to this problem are lightweight artificial intelligence models, model pruning techniques, hardware accelerators including TPUs and FPGAs. Edge computing is also being included to move some computational activities from cloud-based systems to local

devices, which reducing the bandwidth used and the consequent latency.

7.2 Blockchain Scalability and Interoperability

Regarding slow processing times and high transaction costs, both of which impede the expansion of real-time applications for the healthcare industry, conventional blockchain systems including Ethereum struggle as well. Layer-2 solutions including sidechains and state channels, sharding approaches, DAG-based architectures are under investigation as potential means to get beyond these constraints. Further, several blockchain networks and present EHR systems have to be able to interact with one another if they are meant for general acceptance. The process will depend much on standardized protocols and cross-chain communication systems to enable SSSblockchain-based healthcare solutions more accessibility and practicality.

8. Conclusion

The IoT, ML, and blockchain are joining to revolutionize the healthcare industry by letting one monitor patients in real time, precisely diagnose diseases, and safely manage medical data. Although this hybrid approach has great potential to be transforming, some problems have to be fixed. These challenges cover scalability for blockchain, computational efficiency, and privacy for models of artificial

intelligence. Future research should be mostly focused on the optimization of lightweight artificial intelligence models, the development of federated learning methods, and the enhancement of blockchain systems for low-cost, low-speed transactions. The healthcare industry will be able to fully utilize these technologies by means of successful completion of these challenges, which enabling healthcare systems with improved efficiency, security, and patient focus.

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