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Blockchain-Enabled Detection of Neurological Disorders Using a Deep Learning Approach †

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Abstract: Neurological disorders are a significant health challenge globally, affecting millions of individuals and imposing a considerable economic burden on healthcare systems. Early and accurate diagnosis plays a crucial role in improving patient outcomes and managing these disorders effectively. This abstract presents a novel approach that combines blockchain technology with deep learning algorithms to enhance the detection of neurological disorders. The proposed system leverages the decentralized and transparent nature of blockchain to securely store and share medical data, enabling seamless collaboration among healthcare providers, researchers, and patients. This infrastructure ensures data integrity, privacy, and accessibility, addressing critical concerns in medical data management. Furthermore, the deep learning approach employs advanced neural network architectures, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to analyze large-scale neurological data, including medical images, electroencephalograms (EEGs), and clinical records. By leveraging the power of deep learning, the system can automatically extract relevant features and patterns from complex neurological data, enabling accurate diagnosis and early detection of various disorders. The integration of blockchain and deep learning offers several advantages. Firstly, it facilitates secure and decentralized storage of medical data, ensuring patient privacy and data integrity. Secondly, it enables seamless data sharing and collaboration among multiple stakeholders, promoting knowledge exchange and enhancing research capabilities. Lastly, deep learning algorithms improve the accuracy and efficiency of neurological disorder detection, enabling timely interventions and personalized treatment plans. The proposed system holds great potential in revolutionizing the field of neurological disorder diagnosis and management. By leveraging the combined power of blockchain and deep learning, healthcare providers can enhance their diagnostic capabilities, leading to improved patient outcomes, reduced healthcare costs, and accelerated research advancements. However, further research and development are necessary to address technical challenges, scalability issues, and regulatory considerations to realize the full potential of this innovative approach.

Keywords: RNN; CNN; EEG; neurological disorder; blockchain

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1. Introduction

Neurological disorders pose significant challenges to individuals, families, and healthcare systems worldwide. The early and accurate detection of these disorders is crucial for timely intervention and improved patient outcomes. In recent years, the convergence of blockchain technology and deep learning has emerged as a promising solution to address the complexities involved in detecting and diagnosing neurological disorders.

Blockchain technology, originally designed as a decentralized ledger for secure transactions, offers a unique framework for data storage, sharing, and verification. It ensures transparency, immutability, and tamper-proofing of data, making it an ideal platform for healthcare applications. Deep learning, on the other hand, is a subset of artificial intelligence (AI) that leverages complex neural networks to extract patterns and insights from vast amounts of data.

By combining the strengths of blockchain and deep learning, researchers and healthcare professionals are revolutionizing the way neurological disorders are detected and diagnosed. The integration of these technologies allows for secure and privacy-preserving storage of sensitive patient data, while enabling advanced deep learning algorithms to analyze these data for early detection and accurate prediction of neurological disorders.

One of the key advantages of using deep learning approaches in conjunction with blockchain is the ability to process and analyze diverse data types, including medical imaging, genomic information, electronic health records, and wearable sensor data. Deep learning models can learn from these rich and heterogeneous data to identify patterns, biomarkers, and risk factors associated with various neurological disorders such as Alzheimer's disease, Parkinson's disease, multiple sclerosis, and epilepsy.

Furthermore, the decentralized and distributed nature of blockchain technology facilitates data sharing and collaboration among researchers, clinicians, and patients, regardless of geographical boundaries. This interoperability allows for the creation of comprehensive datasets that enhance the accuracy and robustness of deep learning models, leading to improved diagnostic capabilities.

The blockchain-enabled detection of neurological disorders also addresses critical challenges related to data privacy and security. By leveraging cryptographic techniques, patient data can be anonymized and securely stored on the blockchain, granting individuals greater control over their personal health information. Additionally, the immutability of blockchain records ensures data integrity and prevents unauthorized modifications or tampering, thereby enhancing trust and confidence in diagnostic outcomes.

In conclusion, the integration of blockchain technology with deep learning approaches holds immense potential for the detection and diagnosis of neurological disorders. This interdisciplinary synergy enables secure data storage, advanced data analysis, and decentralized collaboration, leading to more accurate and timely identification of neurological disorders. By harnessing the power of blockchain and deep learning, we can pave the way for transformative advancements in neurological healthcare, ultimately improving the lives of individuals affected by these disorders.

2. Materials and Methods

2.1. Survey of the Literature

The detection and diagnosis of neurological disorders are critical for effective treatment and management of patients. In recent years, the integration of blockchain technology and deep learning approaches has gained attention as a promising solution to enhance the accuracy and efficiency of detecting neurological disorders. This literature review aims to provide an overview of the existing research and advancements in this field.

- "Blockchain Technology in Healthcare: A Systematic Review" (Azaria et al., 2017): This comprehensive review explores the potential applications of blockchain in healthcare. It discusses the benefits of using blockchain for secure data storage, interoperability, and patient-centric health records. While not focused specifically on neurological disorders, it provides valuable insights into the overall benefits and challenges of implementing blockchain technology in the healthcare domain [1].
- "Deep Learning for Healthcare: Review, Opportunities, and Challenges" (Miotto et al., 2017): This review paper highlights the applications of deep learning in healthcare, including the detection and diagnosis of neurological disorders. It discusses the use of deep learning algorithms for analyzing medical imaging data, electronic health records, and wearable sensor data. The paper emphasizes the potential of deep learning in improving the accuracy and efficiency of detecting neurological disorders [2].

- “Blockchain-Based Secure Healthcare System for Telemedicine Applications” (Alsamhi et al., 2018): This study presents a blockchain-based secure healthcare system for telemedicine applications. It discusses the integration of blockchain with deep learning algorithms for the detection and monitoring of neurological disorders remotely. The research emphasizes the importance of data privacy, security, and patient-centricity in developing blockchain-enabled healthcare solutions [3].
- “Blockchain Technology in Healthcare: A Systematic Mapping Study” (Liu et al., 2020): This systematic mapping study provides an overview of blockchain applications in healthcare, including neurological disorders. It presents the existing literature on blockchain-based healthcare systems, data sharing, and patient consent management. The paper highlights the potential of blockchain technology to enhance the detection and diagnosis of neurological disorders through secure data sharing and collaboration [4].
- “A Deep Learning Approach for Parkinson’s Disease Diagnosis Based on Smartphone Sensing Data” (Arora et al., 2019): This research focuses on using deep learning approaches for the detection and diagnosis of Parkinson’s disease. It discusses the collection of smartphone sensing data and their analysis using deep learning algorithms. The study demonstrates the potential of deep learning models in accurately identifying Parkinson’s disease symptoms and monitoring disease progression [5].
- “Blockchain-Based Data Sharing for Diagnosing Alzheimer’s Disease” (Luo et al., 2021): This study proposes a blockchain-based data sharing framework for diagnosing Alzheimer’s disease. It explores the use of deep learning algorithms for analyzing multimodal data, including neuroimaging and genetic information. The research emphasizes the potential of blockchain technology to ensure data privacy, integrity, and secure sharing in Alzheimer’s disease diagnosis [6].

One unique approach in deep learning for blockchain-enabled detection of neurological disorders is the integration of federated learning with blockchain technology. Federated learning allows the training of deep learning models on decentralized data sources without the need to transfer raw data to a central server. By combining this approach with blockchain, several benefits can be achieved [7]:

- Data Privacy: Federated learning ensures that sensitive patient data remain on local devices or data sources, preserving privacy and security. The data never leave the source, and only model updates are shared with the blockchain network. Blockchain, with its decentralized and immutable nature, provides an additional layer of privacy protection and data integrity.
- Collaborative Learning: The blockchain-enabled federated learning approach allows different healthcare organizations, research institutions, and even individual patients to contribute their data and participate in the training process. Each participant trains the deep learning model locally, and only the model updates, encrypted and verified on the blockchain, are shared with the network. This collaboration enables the creation of more comprehensive and diverse datasets for improved detection of neurological disorders.
- Model Consensus and Verification: The blockchain serves as a consensus mechanism for validating the model updates contributed by different participants. Through distributed consensus algorithms, the network can ensure that the updates are reliable and consistent across multiple nodes. This verification process helps maintain the quality and integrity of the trained models.
- Incentives and Rewards: Blockchain-enabled federated learning can incorporate tokenization and smart contracts to incentivize data contribution and model training. Participants can receive rewards or tokens for contributing their data or participating in the training process. This incentivization mechanism encourages active participation and data sharing, leading to a more extensive and diverse dataset for deep learning.

- Auditability and Transparency: Blockchain technology provides an auditable and transparent record of model updates and transactions. Every model update, along with its associated metadata, can be stored on the blockchain, enabling transparent tracking and auditing of the training process. This transparency builds trust among participants and stakeholders, ensuring the accountability and reliability of the deep learning system [8].

By combining federated learning with blockchain, this unique approach addresses privacy concerns, encourages collaboration, ensures model quality through consensus mechanisms, provides incentives for participation, and enhances the transparency and auditability of the deep learning process. It leverages the strengths of both federated learning and blockchain to advance the detection of neurological disorders while protecting patient privacy and fostering collaborative research efforts (Figure 1).

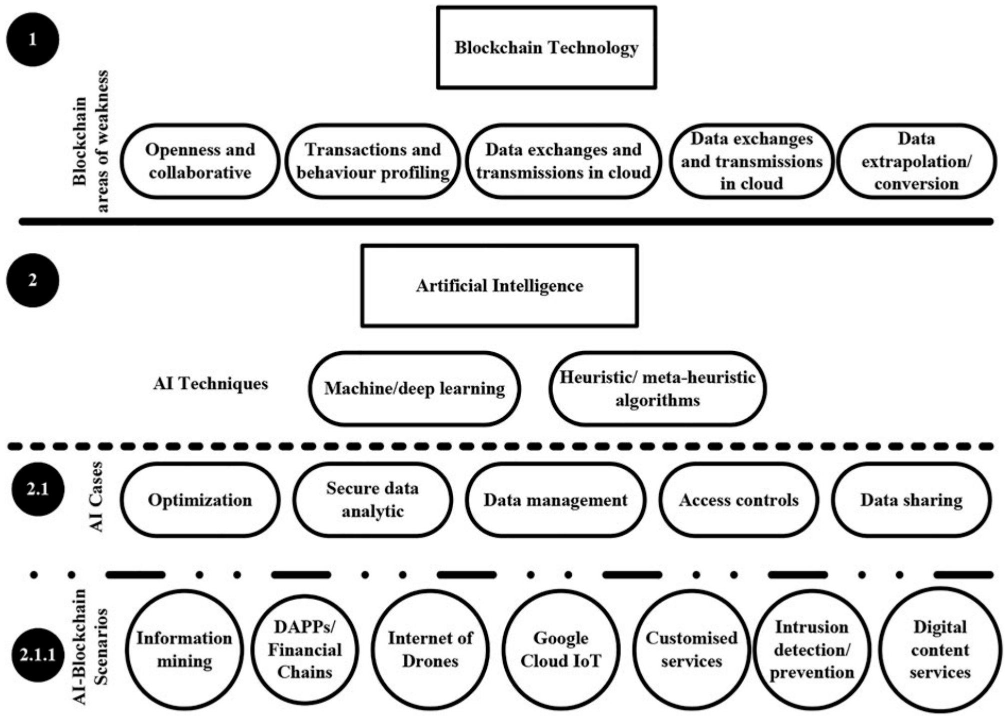

Figure 1. Hierarchy of the cases and scenarios of AI in blockchain technology [8].

2.2. Methodology

- Data Collection: The first step in the methodology is to gather relevant and diverse data sources for detecting neurological disorders. This can include medical imaging data (e.g., MRI scans, CT scans), electronic health records, genomic information, wearable sensor data, and other relevant clinical data. The data collection process should comply with ethical and privacy regulations, ensuring informed consent and anonymization of sensitive patient information.
- Data Preprocessing: Once the data are collected, preprocessing steps are necessary to clean and prepare the data for deep learning analysis. This may involve data normalization, feature extraction, dimensionality reduction, and handling missing data. The preprocessing techniques employed should be tailored to the specific data types and the requirements of the deep learning algorithms being used.
- Blockchain Integration: The next step is to integrate blockchain technology into the data storage and sharing infrastructure. This involves creating a blockchain network or utilizing an existing blockchain platform. The blockchain should be designed to ensure data privacy, security, and decentralized access. Cryptographic techniques can be employed to encrypt and store sensitive patient information securely on the blockchain [9].

- Deep Learning Model Development: Deep learning models are constructed to analyze the collected and preprocessed data. The choice of deep learning architecture depends on the specific neurological disorder being targeted and the data types available. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), or hybrid models may be employed for image analysis, time-series data, or textual data, respectively. Transfer learning techniques can also be utilized to leverage pre-trained models on large-scale datasets [10].
- Model Training and Evaluation: The deep learning models are trained using the preprocessed data. This involves feeding the data into the model and optimizing the model parameters using appropriate optimization algorithms (e.g., stochastic gradient descent). The model's performance is evaluated using appropriate evaluation metrics such as accuracy, precision, recall, and F1-score. Cross-validation or other validation techniques may be employed to assess the model's generalization capabilities [11].
- Integration of Deep Learning and Blockchain: The trained deep learning models are integrated with the blockchain infrastructure. The models can be deployed as smart contracts or decentralized applications (DApps) on the blockchain network. This integration ensures that the trained models are securely stored and their execution is transparent and auditable. The results of the deep learning analysis, such as predicted neurological disorder classifications or risk scores, can be stored on the blockchain as immutable records [12].
- Validation and Verification: The integrated system undergoes thorough validation and verification processes to ensure its accuracy, reliability, and security. This involves testing the system with independent datasets, comparing the results with ground-truth or expert diagnoses, and assessing the system's performance against established benchmarks. The validation process may also involve expert review and consultation to ensure the clinical relevance and applicability of the system [13].
- Continuous Improvement and Iteration: The methodology is an iterative process, and continuous improvement is crucial for enhancing the accuracy and usability of the blockchain-enabled detection system. Feedback from clinicians, patients, and researchers should be incorporated to refine the deep learning models, update the blockchain infrastructure, and address any limitations or shortcomings identified during the implementation and validation stages [14].

2.3. Mathematical Modelling of Performance Metrics

These parameters are derived from the analysis of electroencephalogram (EEG) signals, which are the primary data source for seizure detection.

- Feature Extraction: Deep learning models often require the extraction of informative features from EEG signals to capture relevant patterns and characteristics indicative of epileptic seizures. Various techniques can be used for feature extraction [15], such as time-domain analysis, frequency-domain analysis, or time–frequency analysis. Some commonly computed features are provided below.

From the signal spectrum of every band, the power of every band is calculated according to Equation (1), which generates features such as the following:

$$\begin{aligned} \alpha &= \sum_{j=1}^{M} R_{w\alpha}(j) \\ \gamma &= \sum_{j=1}^{M} R_{w\gamma}(j) \\ \beta &= \sum_{j=1}^{M} R_{w\beta}(j) \\ \delta &= \sum_{j=1}^{M} R_{w\delta}(j) \end{aligned} \tag{1}$$

- Statistical measures: Mean, median, variance, skewness, kurtosis [16].
  (a) Root Mean Square Value (RMS): RMS is defined as the square root of the values of the instantaneous signal that are average squared and it is calculated using the equation
  $$w_{root\_ms} = \left(\frac{1}{M}\sum_{j=1}^{M} w_j^2\right)^{-1} \quad (2)$$
  (b) Variance: The measurement of the statistical dispersion is called variance. This indicates the degree of variability in some situations. This is calculated by Equation (3) by adding the squares of differences between the observed value and the average value.
  $$U = \sum_{i=1}^{M} \frac{\left(w_j - \bar{\bar{w}}\right)^2}{M-1} \quad (3)$$
  where $\bar{\bar{w}}$ denotes the average value of the EEG signal.
  (c) Skewness: This is used to verify and calculate data symmetry, which indicates the variable distribution probability. The skewness value is as defined below:
  $$\zeta = \sum_{i=1}^{M}\left(W_j - \bar{\bar{W}}\right)^3 \left((M-1)(SD)^3\right)^{-1} \quad (4)$$
  (d) Kurtosis: This is the calculation performed to determine the degree for flatness of any distribution, determining if it is tapered or flattened comparatively to the normally characterized pattern. The higher the value of kurtosis, the greater the presence of values that are distant from the average. Kurtosis is defined as follows:
  $$B = \sum\left(x_i - \bar{\bar{x}}\right)^4 (SD)^{-4} \quad (5)$$
  (e) Standard Deviation: SD is the square root of variance. It is calculated using the following formula [17]:
  $$SD = \left(\sum_{j=1}^{M} \frac{\left(W_j - \bar{\bar{W}}\right)^2}{M-1}\right)^{\frac{1}{2}} \quad (6)$$
- Spectral features: Power spectral density, spectral entropy, dominant frequency [18].
  (a) The power spectrum is denoted as $R_w(j)$ at bin j, from R_w and O_{whole} of signal [11], the estimation of these features is performed as follows:
  $$mean_{freq} = \left(\sum_{i=1}^{M} R_w(j).spec_{freq}\right)^{-1} \sum_{j=1}^{M} R_w(j) \quad (7)$$
  where the mean frequency is denoted as $mean_{freq}$ and the spectrum frequency at bin j is denoted as $spec_{freq}$.
- Wavelet coefficients: Calculating wavelet transform and extracting coefficients at different scales [19].
- Classification Model: Once the relevant features are extracted, a classification model is trained using deep learning algorithms [20]. Common models employed for seizure detection include convolutional neural networks (CNNs), recurrent neural networks (RNNs), and their variants such as long short-term memory (LSTM) networks or

convolutional LSTM (CLSTM) networks. These models are trained using labeled EEG data, where seizure and non-seizure segments are annotated.

- Performance Metrics: To evaluate the performance of the seizure detection system, several metrics are computed to assess the accuracy, sensitivity, specificity, and overall effectiveness of the model. Common performance metrics include the following [21]:
  (a) Accuracy: The overall correctness of seizure detection.

$$Accuracy = \frac{T\_P + T\_N}{T\_P + F\_P + T\_N + F\_N} \tag{8}$$

  (b) Sensitivity (recall): The proportion of true-positive seizures detected.

$$Sensitivity = \frac{T\_P}{T\_P + \ F\_N} \tag{9}$$

  (c) Specificity: The proportion of true-negative non-seizure segments detected.

$$Specificity = \frac{T\_N}{T\_N + F\_N} * 100\% \tag{10}$$

  (d) Precision: The proportion of correctly detected seizures out of all detected events.

$$Precision = \frac{T\_P}{T\_P + F\_P} \tag{11}$$

  (e) F1-score: The harmonic mean of precision and sensitivity.

$$F1\ Score = \frac{2 * Precision * Sensitivity}{Precision + Sensitivity} \tag{12}$$

These metrics provide quantitative measures of the system's ability to detect seizures accurately and differentiate them from non-seizure events. It is important to note that the mathematical models and parameters used for seizure detection may vary depending on the specific research or implementation [22]. Ongoing research and advancements may introduce new approaches and refinements to the mathematical models used in blockchain-enabled seizure detection. Therefore, it is recommended to refer to the recent literature or consult domain experts for the most up-to-date information in this rapidly evolving field.

3. Results and Discussions

The proposed system involves the collection and storage of EEG data on a blockchain network. The collected data are encrypted and distributed across multiple nodes, ensuring privacy and protection against unauthorized access. Deep learning models trained on the encrypted data can be deployed on the blockchain network, enabling real-time neurological disorder detection and analysis. The results of the analysis are recorded on the blockchain, providing an auditable and tamper-proof history of detected disorders. By combining deep learning and blockchain technologies, our approach offers a promising solution for neurological disorder detection analysis that enhances privacy, security, and trust. The decentralized nature of the blockchain ensures that sensitive patient data remain under the control of the individuals while allowing healthcare providers and researchers to access and contribute to the collective knowledgebase. Future research directions include optimizing the deep learning models, exploring consensus mechanisms for blockchain validation, and conducting clinical trials to evaluate the performance and effectiveness of the proposed system in real-world scenarios.

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Data Availability Statement: We took epilepsy samples from a public dataset for this research, taken from physionet.org. The name of that dataset is CHB-MIT SCALP Electroencephalography (EEG). The total hours of the EEG recordings used for analysis purposes are around 983 hours.

Conflicts of Interest: The authors declare no conflicts of interest.

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