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Detection of MRI Medical MRI Images of Brain Tumors Using Deep Learning & Secure the Transfer of Medical Images Using Blockchain

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Abstract: High-level developments in the medical services field have just ushered in a new era of enormous EHR. The EHR framework offers data owners get control over their data and allows them to share it with those who have been granted authorization. Information security and symptomatic cycles are challenging to ensure because of the massive volume of data in the healthcare system. Also, with the help of those images, accurate diagnosis of diseases like brain tumors is a quintessential task for medical specialists as well. So, this paper brings an effective Blockchain-based deep learning model to secure the network of transfer and also accurately diagnose brain tumors with an effective deep learning model. The following are the main stages involved: a) Secure data sharing network via Blockchain b) creating smart contracts for better trust between the organization and finally use that dataset to effectively c) classify the brain tumor in a much more effective way. Experiments show that the suggested model outperforms other current models on a variety of metrics.

Keywords: Brain Tumor, Blockchain, CNN, Classification, Detection, Electronic Health Record, IFPS, Smart contracts

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1. Introduction

In machine learning, data is a valuable resource. Preprocessing approaches for improving study conditions can also be employed with the data [1]. Interviews, questionnaires, surveys, and studies can all be used to collect data, or data can be generated electronically through the internet. In Machine Learning(ML), both the quantity and quality of data improve efficiency, classification, and prediction rates. ML models play an important role in healthcare, transportation, e-commerce, and marketing. Data has expanded in volume as a result of the expanding needs, and it is now stored on centralised servers. These centralised servers' data need to be bought for a price. This reduces the research's quality. The centralised server is also prone to failure, lowering the data's reliability. With blockchain, you get a decentralised database without sacrificing data security. Users can readily access data in a decentralised database. A dispersed network of connecting nodes is what blockchain technology is [2]. The distributed ledger, which stores all transaction information, is copied by each node in the Blockchain network [3]. MData is simple to incorporate into machine-learning algorithms. Outside of the banking business, blockchain has demonstrated its diversity and capacity.

As per Critical Analytics statistics, cybersecurity breaches peaked in 2021, exposing a record amount of protected health information on patients. Healthcare attacks harmed 45 million individuals in 2021, up from 34 million in 2020. Healthcare organisations reported nearly triple the number of breaches to the US Department of Health and Human Services in three years, from 14 million in 2018 to 34 million in 2019. The entire study of breaches that occurred over numerous years is depicted in Figure 1.

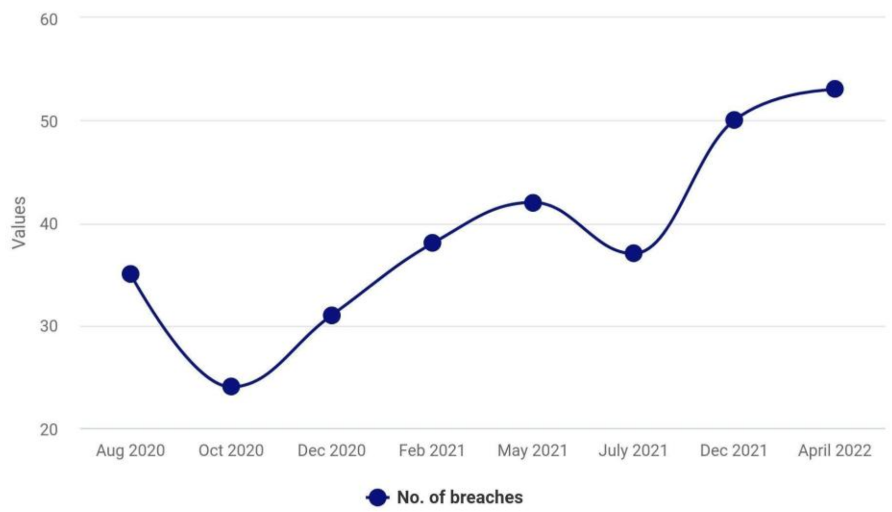

Figure 1. An overall analysis of breaches over the year 2020-2022.

By 2020, the total number of people affected has increased by 32%, suggesting that each year, more records will be exposed. Despite only increasing by 2.4 per cent from 663 in 2020 to 679 in 2021, the total number of breaches reached new highs. “Whether the attack vector is ransomware, credential harvesting, or stealing devices, the healthcare industry is a prime target for attackers looking to monetize PHI and sell on the Dark Web or hold an entity ransom unable to deliver patient care." stated John Delano, vice president of Christus Health and a healthcare cybersecurity strategist at Critical Insight. Healthcare organisations need to be cautious in 2022 not only about their internal cybersecurity but also about other vendors who may have access to Based on thorough research of the healthcare blockchain and a strong approach to healthcare management, this paper provides a healthcare smart contract system that can manage patient data and simplify complicated medical processes [5]. We introduce a blockchain-based healthcare management solution based on cutting-edge blockchain research in

1.1 Key Highlights

This paper focuses on bringing a secure framework and also diagnosing the disease using a deep learning model. Following are the main objectives involved in the study:

- Create a safe system for transferring EHR data across hospitals and other medical facilities.
- Create trust between multiple healthcare organisations with the use of smart contracts.
- Once the images were received, they were preprocessed for even better quality before being subjected to deep learning processes.
- DWT was used to extract features, while PSO was used to select them.
- The CNN model was used to classify MRI brain pictures.

Organization of paper: Since the introduction to blockchain-deep learning portion of healthcare was already covered in Section 1, the remainder of the study is organised as follows: Section 2 depicts the

networks and data. In our industry, we're seeing more cybersecurity awareness and proactive methods, but we still have a long way to go. According to the findings, healthcare organisations should build a comprehensive risk management program and categorise their business associates based on the sorts of data they have access to.

healthcare. As seen by some projects in many nations and economies, governments and large corporate sectors are taking a more active role in digitising healthcare systems. The key to success is for each company's DNA to include blockchain, distributed ledger technology, and other easily available technologies [6,7,8].

literature research, Section 3 depicts the general architecture of the study, Section 4 illustrates the performance analysis, and Section 5 depicts the conclusion.

2. Literature Review

In Sammeta&Parthibhan (2021) [9], many stages of operations are described, including encryption, optimal key generation, hyperledger blockchain-based safe data management, and diagnostics. Using the approach provided, the user can regulate data access, authorise hospital authorities to read and write data, and notify emergency contacts. For encryption, the SIMON block cypher algorithm was utilised. Simultaneously, the SIMON technique's optimal key generation was improved using a group teaching optimization algorithm. Medical data was also shared through a multi-channel hyperledger blockchain, which keeps patient visit data on a blockchain and allows medical institutions to track

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linkages to EHRs stored in other databases. A variational autoencoder (VAE)-based diagnostic model was used to detect the presence of diseases after the data has been encrypted at the receiving end.

Artificial Intelligence models are used to forecast symptoms of COVID -19, explain how it spreads, and speed up research and therapy using medical data, according to Aich et al. (2022) [10]. Due to the fragmented nature of patient data across the healthcare system, building a robust AI model as well as a generalised prediction model and using it in a real-world environment is difficult. To address the aforementioned difficulties, a solution was suggested based on blockchain and AI technologies. Data access and AI-based federated learning will be protected by the blockchain, enabling the development of a solid model for real-time applications that can use globally.

Bhattacharya et al. (2019) [11] presented a Blockchain-based Deep Learning as-a-Service platform. It is divided into two phases and employs blockchain and deep-learning algorithms to facilitate the exchange of EHR records among a large number of healthcare consumers. The first part describes a lattice-based cryptography-based authentication and signature. In the second step, conserved EHR datasets were used.

Kim and Huh (2020) [12] looked into AI blockchains, noting that blockchain, AI, neural networks, healthcare, and other industries all face obstacles, which is why EHR solutions aren't extensively employed. After EHRs implementation, data flow and verification across hospitals will be accomplished and hence privacy protection will be better in the future. To solve this problem, a blockchain artificial intelligence architecture was introduced for data security and to validate blockchain systems for reliable data extraction, storage, and verification.

Mantey et al. (2022) [13] offered an integrated environment for analysing Electronic Health Records that includes a blockchain and a deep learning ecosystem (EHR). A patient's medical record that is shared between hospitals and other public health agencies (EHR) is electronic health records. Using the technology suggested by Mantey, a deep learning system can function as an agent and review EHR data stored on a blockchain. Patients can receive appointment reminders, diet charts, and other information through this proposed integrated environment.

3. Methodology

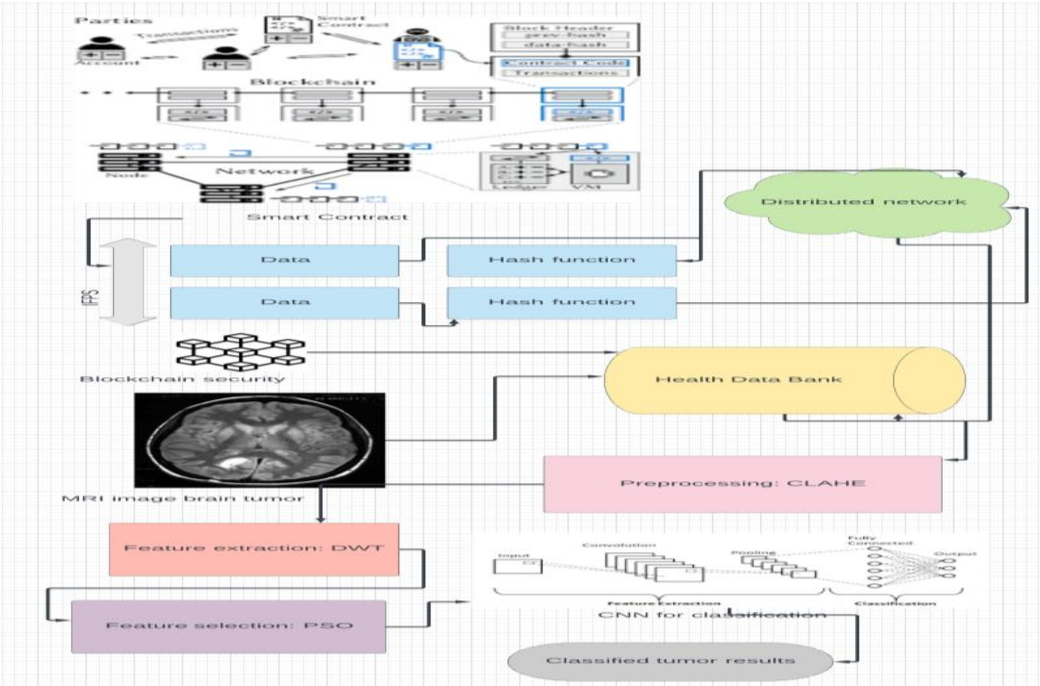

Figure 2 depicts the general design of the proposed framework, with the main steps as listed below. a) Using Blockchain technology to create a secure data exchange network for a variety of healthcare organisations. Hospitals, pharmacies, healthcare diagnostics, and other healthcare organisations are just a few examples. Then to build trust, b) smart contracts are being used among various healthcare organisations. Then once this data is encrypted and sent, the decrypter at the end user access it by decrypting and can use this data (MRI) for further diagnosis of brain tumor. These will further be used for detecting and classifying brain tumors. Following are the sub-stages included in the process. i) Preprocessing of the medical data is performed to eliminate unwanted noise from the images and to improve the quality, CLAHE has been used, ii) feature extraction using Discrete Wavelet Transform (DWT) for extracting quintessential features iii) feature selection using PSO and finally iv) classification using CNN model.

3.1 Smart contracts

It is a sort of digital contract between two parties that is written in executable code and follows specific rules. The Blockchain network makes use of smart contracts to carry out actions depending on them [15]. It allows an organisation to keep track of all transactions that are traceable and irreversible without the involvement of a third party. A smart contract's major purpose is to guarantee security while lowering expenses. Because the smart contract is publicly accessible across the network, users can participate in it. A smart contract's information has three properties: it is (a) immutable, (b) transparent, and (c) always operational.

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3.2 Interplanetary File System(*IPFS)*

The interplanetary file system is a distributed file system that permits users to access and sort data, files, photos, and websites. The protocol's design allows for Internet versioning in the same way that GitHub's repository versioning does. A cryptographic hash is used to assign a unique identification to each file and each block inside it. Duplicates are deleted from the network, and each file's version history is recorded [16,17]. The IPFS workflow is depicted in Figure 3.

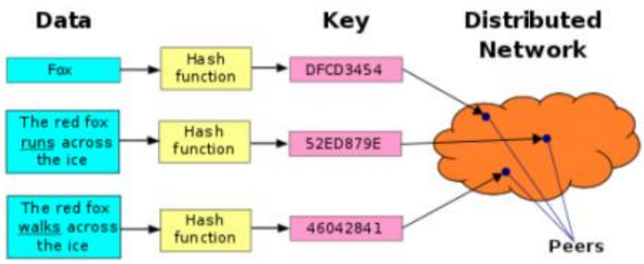

Figure 3. Interplanetary File System (IPFS) functional diagram

Based on MRI data, hospitals exchange the weights of the locally taught neural network. Both the local model weights and the hospital authentication information are stored in the IPFS. On the blockchain ledger, IPFS hashes are recorded. Using blockchain nodes, the global deep learning model computes and aggregates the local model weights. Deep neural networks process the data to improve performance, and new weights are stored in IPFS with hashes in a permission blockchain ledger. Figure 2 depicts the proposed structure for combining blockchain with deep learning models. To begin, all hospitals must submit local model weights, legal retractions, and data collection expenses to the IPFS. According to hospital policy, a customer can request permission to access shared data. A blockchain-based network can help companies with different regulatory restrictions communicate information, and a collaborative deep learning model can help with a brain tumour early detection. The sharing of knowledge among several organisations aids in the development of a more robust DL learning model.

3.3 Data sharing framework & Smart Contract

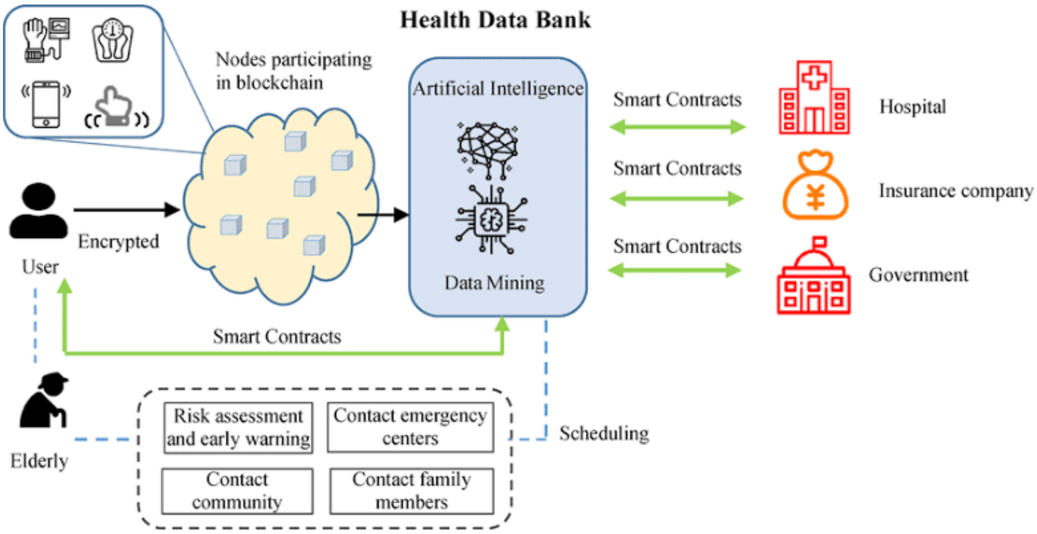

Figure 4. Smart Contract healthcare side architecture

The smart contract (Figure 4) guarantees secure and private data communication between hospitals. It is utilised for a secure data exchange, allowing medical images to be automatically uploaded. It sets parameters following the terms and circumstances of data-sharing agreements.

To communicate imaging data between hospitals, a smart contract [18] is employed. In the blockchain database, IPFS employs hashes to record all local model weights (reference id). Authorized hospitals distribute the weights of locally trained deep learning models via the smart contract. The model can be shared on the blockchain network, thanks to a smart contract. Since the blockchain network is completely decentralised and various parties' data collection contexts are different, only a registered organisation can access the shared weights. The blockchain's openness and trustworthiness among geographically scattered nodes are ensured by the smart contract. This gives the concept new vitality and makes the implementation of smart contracts much easier. Algorithms 1 and 2 show how to use a smart contract to register for a hospital and share data with access control limitations [19].

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Algorithm 1: Data Registration
Contract State ← 1 created
Hospital State ← Ready to Upload Images
h ← is the set of Register Hospitals(H)
h1 ← belongs to the list of hospitals
Restricted access to only h ∈ H
if Hospital is registered & IPFS hash == true then
ContractState ← 1 success Sign
Hospital State ← success approved
create a message of validation for all hospitals
end if
if Hospital is registered & IPFS hash! = true then
Contract revert There is an error in the state.
end if

The RegisterData function is used by the organisation to register its data. All hospitals can access the data after it has been uploaded to the blockchain network with the approval of other institutions. Data can be accessed using the access token. Medical data can be exchanged across organisations and accessed by authorised clients. Algorithm 2 shows a sample smart contract for data sharing. The smart contract specifies the norms of data flow between organisations in this case [21]. The information is digitally signed and belongs to the Register Hospitals' owner (H). The token is created in the blockchain ledger. The usage of a smart contract guarantees that the images sent are from a reliable source. With the signatures of the enrolled hospitals, the smart contract uploads the data to the blockchain network. It also aids in more precise forecasting and decision-making while preserving security [22].

Consider the following two hospitals for a better idea (organizations). The data from these two hospitals have been uploaded to the blockchain network. Assume there are n hospitals in the neighbourhood. Here, the weight of the locally trained model (I = 1,..., N) has been decided by hospitals. The information is tied to a Tx0co transaction that has been signed by hospitals. The data is used to create a secret key and to train the model. The hashes are recorded on the blockchain, a decentralised ledger. A secure data exchange system is depicted in Figure 4. Step 1: For authentication purposes, start the asymmetric key generation operation. Step 2: Before entering the secret data into the certified blockchain network, verify the sender and receiver. Create the data chunks that will

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be broadcast over the network in step three. Furthermore, the generator generates numerous similar-to-the-original-input solutions from noise, and the discriminator determines whether the generated solution is correct or not. The network will always have a reasonable quantity of information, allowing it to check input accurately. Once these records have been collected, they will be passed on to the next level, which is a deep learning model.

3.4 Deep Learning framework

Forward and backward propagation can be used to train neural networks. These methods are used to calculate and update the neuron weights in various neural network layers. [22] The input is provided by F = f(x, w) = y, and the trained dataset D = (xi, yi) is utilised to process the input code x and w parameter vector for a forward propagation procedure for each hospital (xi, yi). The decentralised network distributes the learned weights. L(D, w) = loss is the loss function for the training dataset. D is defined as the dataset and l is the loss function, loss =

$$s = \frac{1}{D}\sum \quad (x_i, y_i)\epsilon DL(y_i, f(x_i, w))$$

The weights of the neural networks are updated for backward propagation using Stochastic Gradient Descent (SGD), which is defined as follows:

$$w^{t+1} \leftarrow w^2 - \eta\Delta_w L(D^t, w^2)$$

The learning rate is shown in Equation (1), The ith indicates how many times the wt parameters have been iterated. Dt⊆D is the hospital mini-batch training dataset. The calculation above is for a single user. To learn a local model and collaborate to develop a global model for each hospital's private dataset v ∈ V shown in Equation (2)

$$w^{t+1} \leftarrow w^2 - \eta\frac{\sum \quad v\epsilon v \;\; \Delta_w L(D^t, w^2)}{|v|}$$

The following are the steps in the deep learning technique for detecting brain tumours from a secure dataset.

3.4.1 Preprocessing

The majority of the images in the datasets considered in this study have low contrast. As a result, a conventional technique known as Contrast Limited Adaptive Histogram Equalisation(CLAHE) helps to boost the contrast of the images. CLAHE (Algorithm3) assesses a histogram of grey values in a contextual zone centred around each pixel before assigning a value to each pixel intensity within the display range [23]. It also employs a preset value known as the clip limit, which aids in the clipping of the histogram before computing the Cumulative Distribution Function (CDF). CLAHE, on the other hand, redistributes those areas of the histogram that exceed the clip limit evenly among all histogram bins.

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Algorithm 3: CLAHE
Step 1: Read the input image.
Step 2: Apply mean and median filter.
f(a,b)= (1/mn) ∑ (s,t)∈Sabg(s,t)
f(a,b) = median(s,t)∈**S**ab{g(s,t)}
Step 3:Find the frequency counts for each pixel value.
Step 4: Determine the probability of each occurrence using the probability function.
Step 5:Calculate cumulative distribution probability for each pixel value.
Step 6: Perform equalization mapping for all pixels.
pval = img (i, j) +1
ieqv(i,j) = ieqvhist(pval)-1
Step 7: Display the enhanced image.

3.4.2 Feature extraction

Due to its multi-resolution analytic capabilities, the wavelet transform is a suitable technique for feature extraction from MRI brain images. It allows for the examination of imagery at multiple levels of resolution. Visual facts can be quickly transmitted using the multi-resolution representation.

To reduce feature vector dimensions and increase discriminative capabilities, we used three levels of (DWT) to extract wavelet coefficients. The statistical features that were extracted are as follows:

a) The mean (M) is calculated by multiplying the total number of pixels in an image by the sum of all pixel values in the image [26].

b) As mentioned in (3) [27], the Standard Deviation (SD) is the second central moment that depicts the future distribution of an observed population and can be used to measure inhomogeneity.

$$\sigma = \sqrt{\left(\frac{1}{mn}\sum_{x=0}^{n-1}\sum_{x=0}^{n-1}\left(f(x,y)-m^2\right)\right)}$$

c) The mean of variance is used to calculate the spread between the integers in each image vector (V). The variance indicates how far each integer in the vector is from the vector mean. The formula (5) [26] is used to calculate the variance.

$$v_1 = \frac{1}{m-1}\sum_{i=1}^{m}\left(A_i - m)^2\right)$$

$$v = \frac{1}{n}\sum_{i=1}^{n} v_1$$

d) As shown in (6) [27], entropy (E) is calculated to describe the randomness of the textural image.

$$E = -\sum_{x=0}^{m-1}\sum_{y=0}^{n-1} f(x,y)\log_2 f(x,y)$$

e) Skewness (Sk) is a metric that measures symmetry or lack of it. The following formula is used to calculate the skewness: (7) [27]:

$$sk = ((\frac{1}{mn})\frac{\sum \quad f(x,y) - m^3}{\sigma^3})$$

f) Kurtosis (Ku) is a measure of the probability distribution of a random variable. It is calculated as follows in (8) [27]:

$$ku = (\frac{1}{mn})\frac{\sum \quad f(x,y) - m^4}{\sigma^4}$$

g) RMS [26] is used to determine the square root of the arithmetic mean of the squares of the data or the square of the function that characterises the continuous waveform.

$$RMS = \sqrt{(\frac{1}{mn})\sum_{x=0}^{m-1}\sum_{y=0}^{n-1} f(x,y)^2}$$

3.4.3 Feature Selection

In 1995, Kennedy and Eberhart developed bio-inspired algorithms as an EC approach [28]. In particle swarm optimization, individual birds are treated as particles in a flock of birds, with a swarm of particles representing a potential solution that will be optimised to a problem. The goal of randomly scattering these particles in the search space is to locate the global optimum of a system. To determine the global optimum of a system, the best personal value pbest and the best personal location of the particle gbest in the swarm are employed. After each repetition, the velocity and location are updated. Figure 5 [29,30] depicts the PSO approach.

Overall pseudo-code of PSO
1. initialize all particles with a random position and velocity in the search space based on the mode 2. while stopping condition is not met 3. for each particle do 4. calculating the fitness of the particles 5. if particle fitness is better than previous then 6. set particle fitness value as new 7. end if 8. if the particle fitness value is better than the current then 9. set fitness value as the new 10. end if 11. end while 12. present solution

Figure 5. Overall pseudo-code of PSO

3.4.4 Classification

In a typical neural network, image scaling is not possible. The image can be scaled in a convolution neural network [31,32]. The convolution layer breaks the original image down into smaller chunks. Each element is individually activated by the ReLU layer. It is not necessary to use a pooling layer. Whether we use it or not, is entirely up to us. On the other hand, downsampling typically takes advantage of the pooling layer. The last layer (i.e., the totally linked layer) calculates the class score or label score value.

Figure 6 shows a block diagram of a brain tumour classification system based on convolutional neural networks. There are two stages to CNN-based brain tumour categorization: training and testing. To categorise the images, they are labelled with terms like tumour and non-tumour brain imaging, among others. The training phase includes preprocessing, feature extraction, and classification using the Loss function to produce a prediction model. First, label the training image collection. Image scaling [33] is a preprocessing technique that alters the scale of an image.

Finally, brain tumours are automatically classified using a convolutional neural network. The brain imaging dataset was provided by Image Net. It is a pre-trained model. To start from the beginning, should train the entire layer (to the conclusion). As a result, a significant amount of time is squandered. It will have an impact on the outcome. Classification stages work around this by using a model that has previously been trained on a brain dataset. Python will only be used to train the proposed CNN's last layer. Training all of the layers at the same time is not a smart idea. The suggested automatic brain tumour classification method [34,35] has a quick computation time and a high level of accuracy as a result.

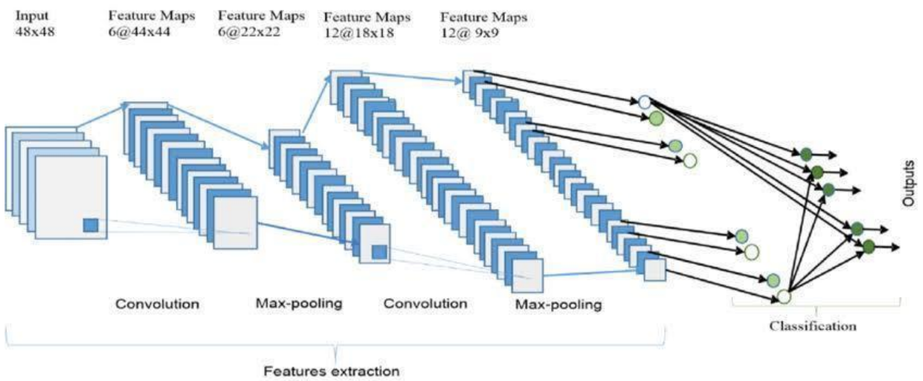

Figure 6. CNN architecture for brain tumor classification

4. Performance Analysis

The smart contract is deployed on a public blockchain using the ganache server. The truffle framework was used to test the ganache server's smart contract. For client-side programming, we also install node.js and the metamask plugin. To save files in IPFS, we used infura Gateway. To guarantee that the smart contract performed effectively, all obligations were double-checked. The hash is registered. A specific volume of gas must be deployed for each contract. The designer has set the maximum amount of gas that can be consumed at 300,000. Two types of gases used are transaction and execution. The amount of gas required to deploy a smart contract on a blockchain is called transaction gas. The quantity of gas used by each function to complete logical operations is known as the execution cost.

Hardware specifications such as 8GB RAM, 1TB HDD, Ryzen 5/6 series CPU, and Windows 10 OS were used to execute the deep learning model, along with software specifications such as PyTorch,

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an open source python library for building deep learning models, and Google Collaboratory, an open source Google environment for developing deep learning models. The accuracy, sensitivity, specificity, recall, precision, F1-score, detection rate, TPR, FPR, computation time, and security of the Blockchain-based deep learning model are compared to other latest models such as VGG16, VGG19, Alexnet, Resnet50, and ensemble learning. Table 1 shows the overall analysis of many models in terms of accuracy, sensitivity, and specificity. Figure 7 depicts a graphical representation of different models versus the proposed method, with the proposed model surpassing the others by 0.96 accuracy, 0.98 specificity, and 0.98 sensitivity.

Table 3. Overall analysis under accuracy, sensitivity, specificity

Models	Accuracy	Sensitivity	Specificity
VGG16	76	81	83
VGG19	81	85	87
Alexnet	83	89	89
Resnet50	74	83	86
Ensemble learning	86	89	91
CNN-blockchain	96	98	98

Figure 7. Models vs Accuracy, Sensitivity, Specificity

Table 2 depicts the overall analysis under precision, recall and F1-score. Figure 8 depicts a graphical representation of various models over the proposed method in which the proposed model outperforms better than other models at precision (0.95), recall (0.86), and F1-score (0.93).

Table 3 shows the overall analysis under detection rate, TPR and FPR. Figure 9 depicts a graphical representation of various models over the proposed method in which the proposed model outperforms better than other models at detection rate (0.93), TPR (0.91), and FPR (0.9).

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Table 2. Overall analysis of precision, recall and F1-score

Models	Precision	Recall	F1-SCORE
VGG16	79	72	77
VGG19	82	77	74
Alexnet	78	72	71
Resnet50	71	73	75
Ensemble learning	87	84	88
CNN-blockchain	95	86	93

Figure 8. Models vs Measures like Precision, Recall and F1-score

Table 3. Overall analysis of detection rate, TPR FPR

Models	Detection rate	TPR	FPR
VGG16	80	74	26
VGG19	83	73	27
Alexnet	76	74	26
Resnet50	70	75	25
Ensemble learning	85	86	14
CNN-blockchain	93	91	9

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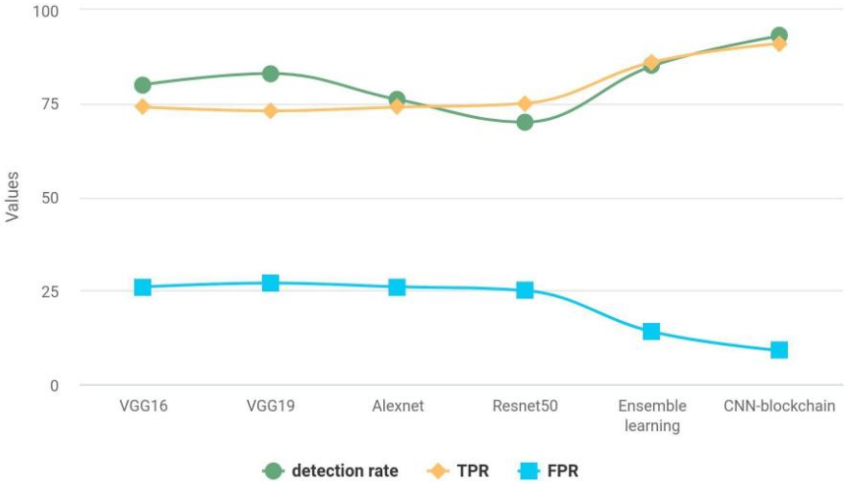

Figure 9. Models vs Measures like detection rate, TPR and FPR

Figure 10 (a,b,c) illustrates the graphical representation of various Blockchain frameworks with respect to computation time, security and finally deep learning model with respect to computation time.

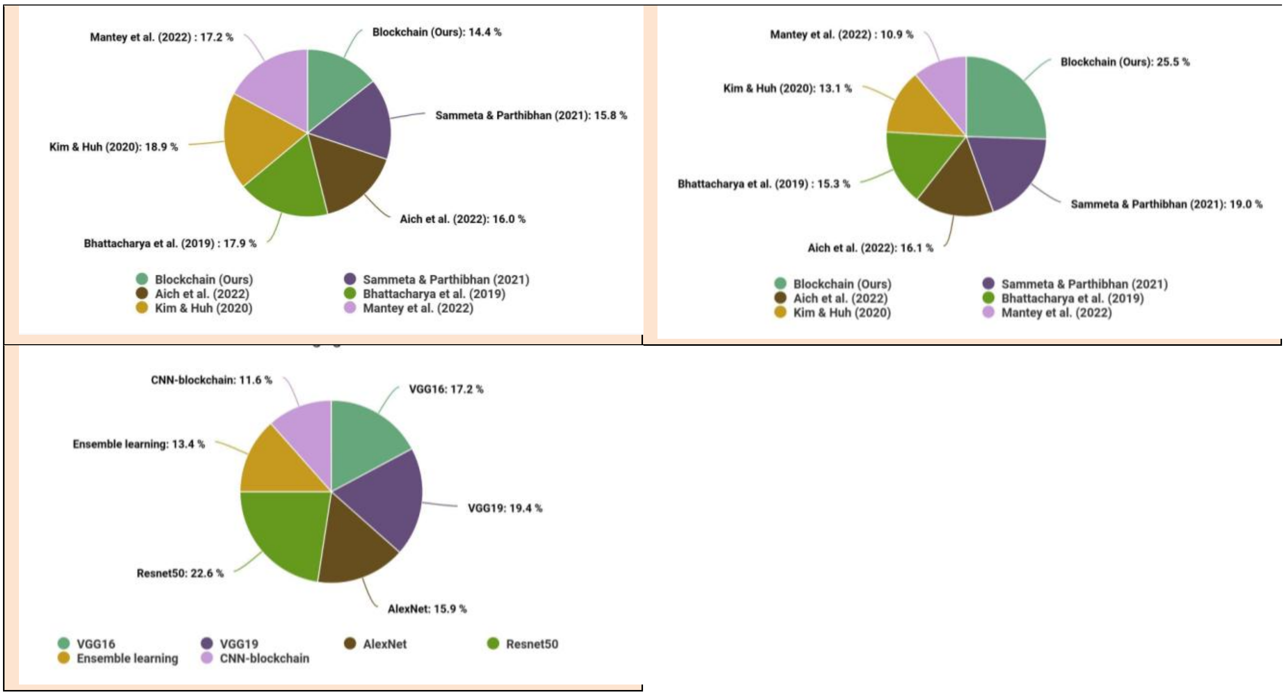

Figure 10. Models vs a) Blockchain framework vs Computation time, b) Blockchain framework vs Security and c) Deep learning framework vs Computation time

5. Conclusion

This paper brings an effective utilization of Blockchain over healthcare in which it depicts the importance of data share and trust between organizations in order to protect against data breaches. Also, this paper brings the importance of deep learning for effectively classifying the brain tumor types from the medical data which is received as well in the most accurate way. This paper will be also useful for other research specialists to dig deep and understand various approaches and try to integrate other emerging technologies for solving issues in the medical field.

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