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Secure Medical Imaging Data using Cryptography with Classification

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ABSTRACT

Medical imaging data is increasing day by day which requires improved applications that perform accurate diagnoses. Secure medical imaging data plays a critical role in current times. Still, today it is a complex task to maintain data privacy, so this study's main objective is to solve this problem. In this research, firstly, secure the medical imaging data using the cryptography Advance Encryption Standard (AES) algorithm. In this process, input images are encrypted and decrypted using public key cryptography and supplied as input to the pre-trained convolutional neural Network such as Alex-net. The model comprises 25 layers such as convolutional, batch-normalization, ReLU and max-pooling, etc. The classification between the tumor and healthy images has been performed using the SoftMax layer. The performance of the proposed model has been tested on the publicly available BRATS-2020 Challenging dataset. The proposed model achieved up to 99.71% accuracy and 97% F1- scores, which are far better as compared to the latest published research work in this domain.

Keywords: *Image Classification; Preprocessing; Features extraction; Cryptography; MRI images*

1. INTRODUCTION

A brain tumor, also known as an intracranial tumor, is a mass of abnormal tissue in which cells grow and divide uncontrollably, seemingly unchecked by the systems that keep normal cells under control. Brain tumors develop when the DNA of cells in or around the brain undergoes alterations [1]. DNA contains the information for how a cell should function. The alterations instruct the cells to grow rapidly and continue alive, even though healthy cells would ordinarily perish. This produces several new brain cells. Brain tumors are the most dangerous disease, and in their most severe form, they can be fatal. If brain tumors are incorrectly identified, physicians will provide the incorrect treatment, decreasing the patient's probability of survival [2]. The correct diagnosis of a brain tumor is essential to determining the most effective treatment for it and helping patients live longer healthier lives. The computer-aided systems for locating tumors and the convolutional neural networks have been very successful and have advanced the field of machine learning significantly. The patient's medical information is securely transmitted to the healthcare system [3]. To prevent unauthorized access, it is essential to ensure data confidentiality and trustworthiness throughout the medical treatment, beginning with the sensors. Suitable encryption techniques used for medical systems. In today's digital period, almost every device is connected to the Internet or cognitive Internet of Things (CIOT). Thus, it threatens the security of these devices connected to the internet. So, we need to reduce these challenges by adopting efficient approaches and techniques in the Privacy, detection, and verification process where Privacy is at significant risk. Traditional methods of securing the data are at high risk because they are network-based methods without any password or even without any other type of security which are not as efficient as the cryptographic methods [4]. Cryptographic techniques mean encrypting and decrypting any medical data. Many securing techniques are available, but we need to be effective and reliable about security and Privacy to minimize security challenges. In our approach, the medical images that require high security can be encrypted and shared with the recipient and the recipient can decrypt and use it [5]. Medical Data Management on Cryptography with Privacy. However, each has its limitations. The problem Statements are secure our personal and medical data plays a critical role in current times, but today, it is the complex task of maintaining data privacy, to solve this problem [6]. The problem of the previous research is that the information in the local database might be changed or removed, which will damage the availability of data, so we use a cryptography method that is more secure than the local database method. We solve this by proposing a privacy-maintaining medical data stage centered on cryptography. The information is encrypted and kept in a federation blockchain, and an information user wants to get the decryption key from a data owner, as shown in Figure 1.

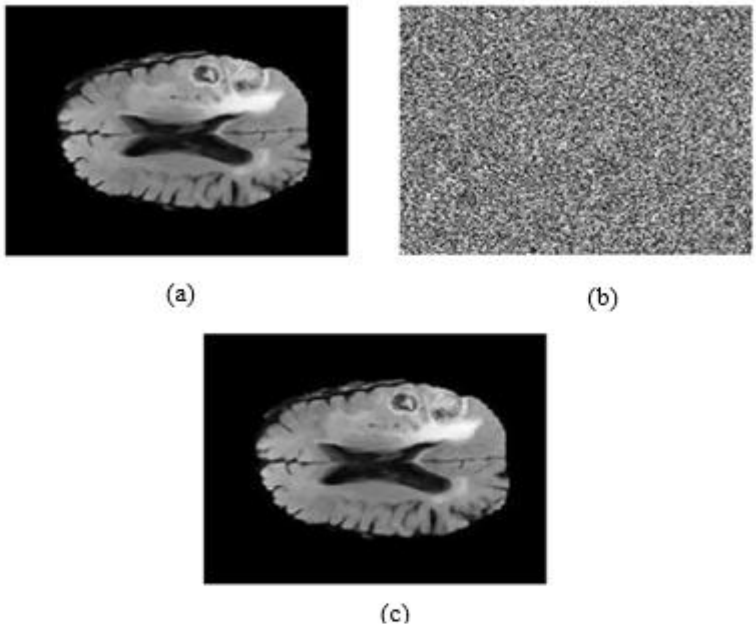


Figure 1: Core Contribution Steps of the Proposed Methodology

Cryptography technology is a software platform that digitally records transactions that cannot be manipulated. In cryptography technology, doctors, nurses, and other providers take health information from a common database [6]. Doctors will research new drugs and treatment therapies for the disease and share the results. Cryptography will allow biologists, intensivists, pharmacists, biologists, radiologists, and other providers to work more efficiently with the healthcare spectrum. The critical concept of cryptography is decentralization [7]. With no single-point failure, this decentralized concept provides high security and robustness stored. Cryptography can detect pandemics, make users rapidly aware of drugs, and during treatment, it can fight infectious diseases by protecting user privacy. Discover the symptoms of COVID-19; the information should be put away on a decentralized network and safely share the latest patient record [8]. To form the newest patient data, it distributes the training work to train the best patient model. Through a decentralized Network, to secure the data. Cryptography network systems help patients, physicians, and healthcare institutions with patient record access and provide services in medical IoT protection management, payment processing, clinical data verification, financial audit exchange, and transparency. In this COVID-19 epidemic, introduce cryptography as an emerging technology that ensures the Privacy and security of health data and provides tools for patient diagnosis, testing, screening, and exchange of infection prevention and control of information with patients and the public, as required for personal safety appropriate safety measures are provided. This COVID-19 –creating a cryptography platform will facilitate registry sharing collaboration between healthcare stakeholders with the necessary information, and both are effectively available. For Example, by giving the patient an identifier and creating an intelligent agreement between professionals and patients that ensures that the combined data is accurate and thus with faster diagnosis efficiency will increase. At the same time, patient security and Privacy will be secured [9]. Information and communication technologies (ICT) and Networks allow healthcare institutions should be digitized and decentralized, and with digitized healthcare ecosystems, services should be provided to patients. Applying a cryptography network can improve information security management in the healthcare industry; while maintaining data security, healthcare data can be transferred and analyzed. We propose a cryptography network so that the authorities can ensure social distancing by allowing a certain number of people in a particular area at a specific time [10].

The main contributions of the research are:

1. The original medical imaging data are secured by applying an AES algorithm.
2. The decrypted images are pre-processed through data augmentation in terms of vertical and horizontal flipping.
3. After augmentation, deep features are extracted from the original and augmented images based on the pre-trained Alex-Net. After feature extraction, the SoftMax layer is used to classify the healthy/abnormal MRI slices more accurately.
4. The desktop-based GUI is developed for real time classification of the brain tumor. In this application, firstly original MRI slices are passed to proposed methods steps such as encryption, decryption, feature extraction, and classification.

The article's organization is as follows: Related work of brain tumor is elaborated in section 2, presented the methodology in section 3, results and discussions are mentioned in section 4 and overall work concluded in the section 5.

2. RELATED WORK

Several works have been done for the detection of brain tumor segmentation and classification. Some of the recent techniques are discussed in this section. Several cryptographic methods can be used to secure the medical images without any external interception [11]. In medical research, particularly involving patient data, ensuring patient privacy, and adhering to ethical considerations are paramount. Several measures are typically implemented to address these concerns and comply with data protection regulations [12]. Reddy et. al [13] proposed the algorithm, Diffie–Hellman key, and the advanced encryption standard to protect medical data and achieved an accuracy of 87%. Lakshmi et. al [14] reviewed the RSA algorithm as an asymmetric encryption technique that safeguards the images before transferring them. It is one of the most extensively used encryption tools. Mohammad et. al [15] proposed an existing blockchain-based method, that is used to secure the network for the detection of brain tumors. Balamurugan et. al [16] proposed LuNet classifiers are the deep learning technique and introduced the hybrid approach achieving 99.7% accuracy. Shahzadi et. al [17] proposed the hybrid CNN with Long-Short Term Memory (LSTM) network to detect brain tumors. The system was tested using data from the 2015 BRAT dataset. VGG-16 has greater classification accuracy than those extracted from AlexNet and ResNet.

Amin. J et. al [18] proposed a method consisting of three phases for the detection of the brain tumor such as classification, localization, and segmentation. In the classification phase, J. Qnet proposed that consists of four layers i.e., Dense, Dropout, and flattened layer for the classification of brain tumors. After that the classified images pass to the ONNX -YOLOv2tiny model for the localization of brain lesions. After the localization the localized images are segmented by using the proposed U-net model. This method is evaluated on the BRATS-2020 dataset providing the accuracy of 0.96 and 0.98 respectively. Amin.J et.al [19] Segmentation performed using K-mean clustering and for the classification GWF, HOG, LBP and SFTA features extracted from segmented images. Used these features then create fused feature vector. Fused feature vector passed to the random forest classifier. Proposed method is tested on five benchmark data sets such as BRATS 2012, BRATS 2013, BRATS 2014, BRATS 2015 and ISLES 2015. BRATS 2015 achieve 91% accuracy and 100% sensitivity is achieved on BRATS 2012, 2013, 2014 and ISLES 2015 data sets. Amin. J et.al [20] proposed method Support Vector Machine (SVM) classifier is applied with different cross validations on three benchmark datasets such as Harvard, RIDER and Local. The method achieved average 97.1% accuracy, 0.98 area under curve, 91.9% sensitivity and 98.0% specificity. It can be used to identify the tumor more accurately in less processing time as compared to existing methods. Amin.J et.al [21] proposed deep LSTM model having four layers is utilized for classification. The results are validated on different versions of BRATS datasets (BRATS 2012–15, 2018) and SISS-ISLES 2015 dataset. Achieved 1.00 on 2012 synthetic, 0.95 on 2013, 0.99 on 2013 Leader board, 0.99 on 2014, 0.98 on 2015, 0.99 on 2018 and 0.95 on SISS-ISLES 2015. Sharif, M et.al [22] proposed triangular fuzzy median filtering for segmentation ST features are passed to extreme learning machine (ELM), and regression ELM for tumor classification BRATS 2012, 2013, 2014 and 2015 challenging datasets used for evaluation and achieved 0.99 DSC on BRATS 2012, 0.99 DSC on BRATS 2013, 89.3 DSC, on 2013 Leader board, 89.3 DSC, on BRATS 2014 and 95.3 DSC on BRATS 2015 databases. Kurdi et.al [22] proposed Harris Hawks optimized convolution network (HHOCNN) in identifying the exact tumor region and hidden edge details with minimum computation complexity features are extracted from the segmented region, which is classified by applying a convolutional neural network

(CNN) and accuracy to 98% achieved on the Kaggle dataset. . Amin. J et.al [23] proposed method for the enhancement of the lesion, features extraction, selection, and classification methods. These are used for feature extraction and fusion by using HOG (shape), SFTA and LBP (texture) based features. Evaluate three publically available BRATS databases and achieve the accuracy of 99%. Khan et.al [24] used the pre-trained CNN model EfficientNetB0 with accuracy to 95.14, 94.89, and 95.94%. Ramtekkar et.al [25] performed preprocessing, segmenting, extracting features using CNN classifiers detect brain cancers with accuracy of 98.9%. Baji, F. S et.al [24] performed classification of 30 MRI pictures use the approach of CNN with accuracy of 87%. Abiwinanda et.al [26] performed the CNN with any prior region-based segmentation with accuracy of 84.19%. Seetha et.al [27] proposed the classification of brain tumor using Convolutional Neural Networks (CNN) classification with accuracy of 97.5%. Chavan et.al [28] performed GLCM texture feature extraction method. The extracted features determined the class of tumor with accuracy of 96.15%.

3. METHODOLOGY

The proposed methodology selected medical images for encryption and decryption because encryption and decryption make the medical images securable in the cryptography technique. Take input images, apply robust encryption techniques, and then use a decryption algorithm. Encryption can encrypt the images and hide them from unauthorized use; similarly, decrypt them to make them usable. Hence cryptography is considered a popular security trait due to its efficiency, accuracy, ease of use, uniqueness etc. cryptography satisfies all these features with good scores. The proposed methodology for secure medical data and classification of MRI images can be illustrated in Figure 2.

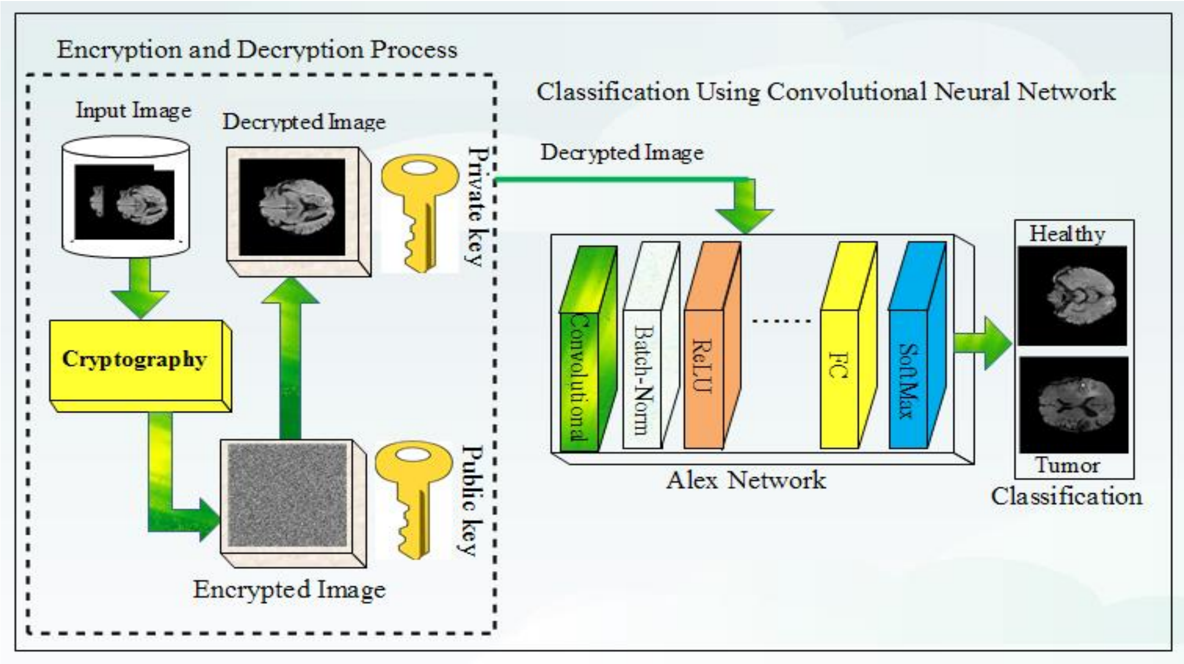


Figure 2: Proposed Methodology for the Secure Medical Data and Classification (MRI images)

MRI is one origin of brain tumor classification; however, according to the variance and difficulty of tumor s utilizing MRI (Magnetic Resonance Imaging) is reasoned to be a challenging process 35 in children's brain tumor classification. [29] The brain tumor system classification is divided into four steps: MRI Preprocessing, Segmentation, Feature Extraction, and Classification step, respectively. In the first step of MRI preprocessing, the first duty is to knock out the MRI sound that may affect light reflections or imprecision in the imaging medium. In Segmentation, segment the tumor area. In Feature Extraction, the features related to MRI (Magnetic resonance Imaging) images will be captured and saved for the classification process in an image. Lastly, in the classification stage, the classifier defines the brain tumor kind.

MRI Dataset used for secure medical data and classification named as BRATS2020 dataset, having two classes tumor and non-tumor slices. BRATS has always been focusing on the evaluation of state-of-the-art methods for

the segmentation of brain tumors in multimodal magnetic resonance imaging (MRI) scans. BRATS2020 utilizes multi-institutional pre-operative MRI scans and primarily focuses on the segmentation.
BRATS 2020 has 335 patients such that each patient contains 155 slices. Every patient has 155 MRI slices with a dimension of 240 × 240 × 155. The detailed description of dataset is illustrated in Table 1.

Table 1: Dataset Distribution Details for Training and Testing Phase

Dataset	Training	Testing
BRATS-2020	25,962	25,962

The Alex Net in MATLAB is broken on the Subset of a database of ImageNet; it can classify thousand+ item classes (for example, Cellphone, Laptop, book etc.). However, they aren't explicitly well-skilled, and the input size of Alex Net is 227 × 227 × 3, so resizing the unique Image to 227 × 227, low resolution can damage the knowledge stored in the actual Image. It contains high-level data of an image like Shape, Texture, Color, and Contrast. Texture study is a necessary variable of human visual awareness and machine learning System. It is operated efficiently to upgrade Precision of diagnosis method by choosing important structures. We use Alex net algorithm used for trained learning images. The brain tumor s in cases of; cropped images and uncropped images, the perplexity matrix for every situation (if cropped, tumor Slice segmented) were created, along Number of Images Tumor Slices are 276 and non-Tumor are 223 Total are 499. [30] In common, to make use of these created perplexity matrices we can compute the accuracy, sensitivity, Precision, and specificity, to calculate how rightly the brain tumor is listed. The generated perplex matrix, four statistical indexes are measured to estimate the presentation of the approved classification system.

A deep Convolutional Neural Network that classifies 1.3 million high-goal ImageNet Set photos into 1000+ classes (CNN). The test data indicates top-1 and top-5 blunder rates of 39.7% and 18.9%, significantly better than the prior best in class results. The 60 million-factor, 500,000-neuron Neural Network has 5 convolutional layers, 2 globally connected layers, and a 1000-way delicate max. non-immersing neurons and convolutional net GPU performance accelerate preparation. Dynamic layer management reduces overfitting. For the classification of MRI images, transfer learning is used. A pre-trained AlexNet model is utilized which is a 25 layers neural network. The Alex Net model is used in MATLAB is broken on a subclass of Image Net database, and it can classify 1000 objects of the classes. Load the latest images as an image data store and unzip. An image data-store object, Image data-store designs the images are established on file names automatically and save the information. During practicing of a convolution neural network, an image data-store entitles to save big image data, along with information that does not suit in memory and accurately reads lots of Image. Break down the information in training verification data sets. Load the Pre-trained Alex Net Neural Network. Deep Learning Toolbox™ model is necessary to run Alex Net Network. Alex Net is capable of classifying images into 1000 items of classes, like computer, refrigerator, pencil, also numerous animals. It recognizes most images of the objects because it is trained on one million images to classify or categorize, resulting in memorizing affluent characteristics delineation for wide range of images. To show an interactive coordinated envision of network design and complete information about the network layer. Concluding three layers of preordained network net reconstruct for 1000 group [31]. These three layers should adjust for latest classification issues. Except the last three, extract all layers from pre-ordained Network. According to the new data, specify options of new fully connected layers. Fully linked layers, the soft-max layer, and the classification layers transmission of layers to latest classification task by renewal the end three layers. The number of classes in latest information, fit the complete linked layers to have equal size. Increment the WeightLearnRateFactor and BiasLearnRateFactor values of the completely connected layer, read quick latest layer in transferred layers. The Network need Input image of size 277-by-277-by-3, but Image in images data-store have various sizes. Undoubtedly resizing the training image, we make use of an augmented images data-store. Data augmentation support keep the Network from remembering, also overfitting the correct information of training image. Without operating further data augmentation to automatically reshape the validity of images, use an augmented image data-store without outlining any increased preprocessing tasks. To ease knowledge in transferred layers, set primary learning quality to minor rate. In preceding step, boost learning quality issues for completely linked layer to trigger learning in the latest last layer [32]. The architecture of AlexNet is illustrated in Figure 3.

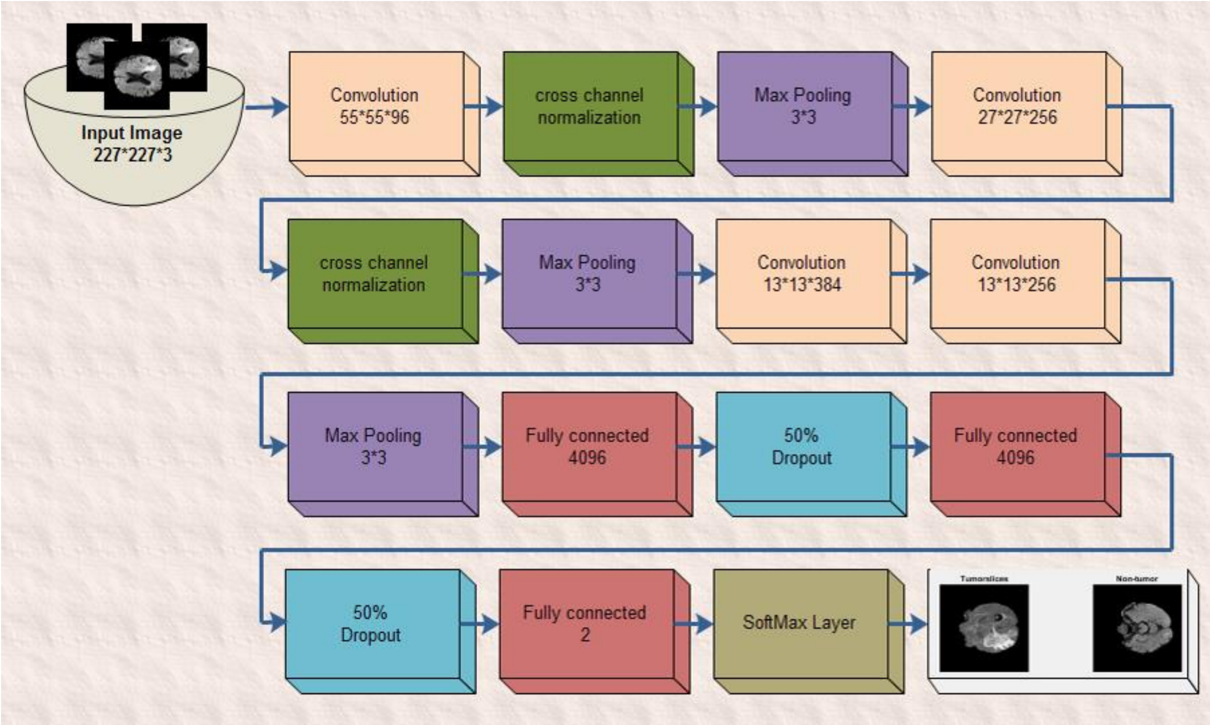


Figure 3: Architecture of AlexNet

The goal behind this is three folds. Firstly, Alex Net can differentiate thousands of kinds of items, yet they are not prepared precisely for petal identification. Besides, the info size of Alex Net is 227 × 227 × 3, we need to resize the genuine picture to 227 × 227, and such sort of low-resolution may hurt the data contained in the real picture. It is the kind of method that contains higher-level information of an image such as color, texture, Shape. Texture explores an essential parameter of human visual observation and machine learning structure [33]. It is used efficiently to improve the accuracy of diagnosis system by choosing flat and such a huge number of prominent features. Secure data using cryptography of medical data consists of the following major phases as depicted in following Figures 4,5 and 6.

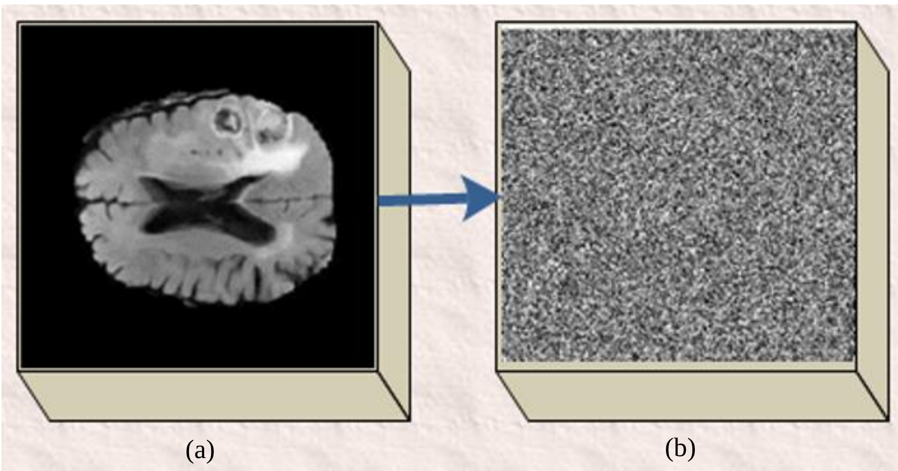


Figure 4: Input Image Converted into Encrypted Image (a) Input Image (b) Encrypted Image

In phase 1, select the Input Image and it converts into encrypted image using the Advance encryption standard algorithm to make the medical data secure, hide them from unauthorized user shown in Figure 5.

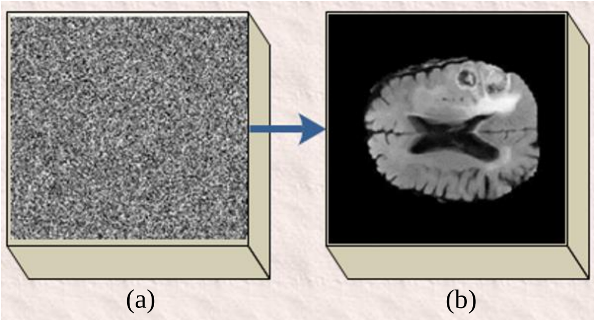


Figure 5: Encrypted Image Converted into Decrypted Image (a) Encrypted Image (b) Decrypted Image

In phase 2, the encrypted image can be decrypted, and it converts into decrypted image using the Advance encryption standard algorithm for the authorized user shown in Figure 6.

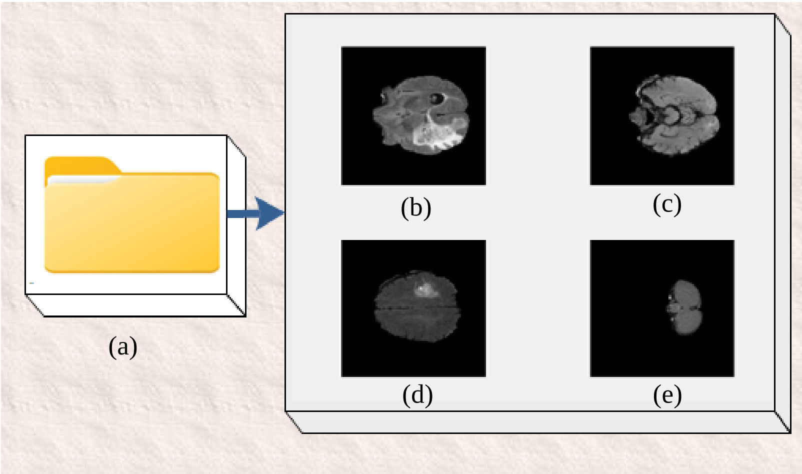


Figure 6: Dataset Classification (a) Dataset (b) Tumor Slices (c) Non-tumor (d) Tumor Slices (e) Non-tumor.

In phase 3, Dataset which is passed to the model AlexNet and the decrypted image can be classified into two classes named as tumor and non-tumor slices shown in Figure 7.

Results	
Validation accuracy:	100.00%
Training finished:	Reached final iteration
Training Time	
Start time:	19-Feb-2021 16:46:04
Elapsed time:	17 min 19 sec
Training Cycle	
Epoch:	6 of 6
Iteration:	204 of 204
Iterations per epoch:	34
Maximum iterations:	204
Validation	
Frequency:	3 iterations
Other Information	
Hardware resource:	Single CPU
Learning rate schedule:	Constant
Learning rate:	0.0001

Figure 7: Results of Classifying the MRI Images

In phase 4, Dataset which is passed to the model AlexNet can generate the results and achieve the validation accuracy 100%. Training can be reached at final iteration. 6 epochs used in training cycle and the learning rate is 0.001 shown in Figure8.

4. RESULTS AND DISCUSSION

Calculations test system accuracy. Ground truth analyses findings. BRATS-2020 challenging dataset [34, 35] analyses the technique. 335 BRATS-2020 patients have 155 slices. We evaluate performance using accuracy [36]. Ground truth inputs determine image accuracy. This section compares our proposed method's database correctness to previous cryptographic approaches.

a) Accuracy

$$\frac{(\mathbf{T+ive}) + (\mathbf{T-ive})}{(\mathbf{T+ive}) + (\mathbf{T-ive}) + (\mathbf{F+ive}) + (\mathbf{F-ive})} \; \mathbf{x\,100} \quad \ldots \quad (1)$$

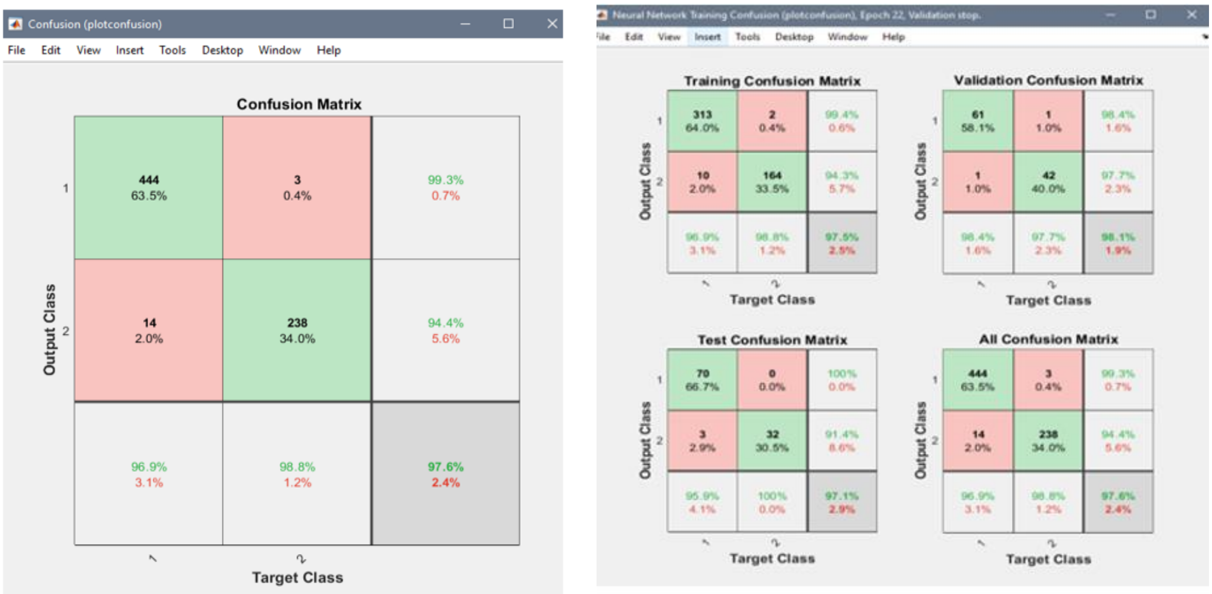
b) Sensitivity

$$\frac{\mathbf{TP}}{\mathbf{TP + FN}} \; \mathbf{x\,100} \quad \ldots \quad (2)$$

c) Specificity

$$\frac{\mathbf{TN}}{\mathbf{TN + FP}} \; \mathbf{x\,100} \quad \ldots \quad (3)$$

We examined the image database and compared algorithm findings to relevant papers. These comparisons show if our technique improved sensitivity, specificity, and accuracy in distinct datasets. Our image dataset approach is accurate and specific. Recall, Precision, Specificity, and Accuracy as shown in Figure 9.



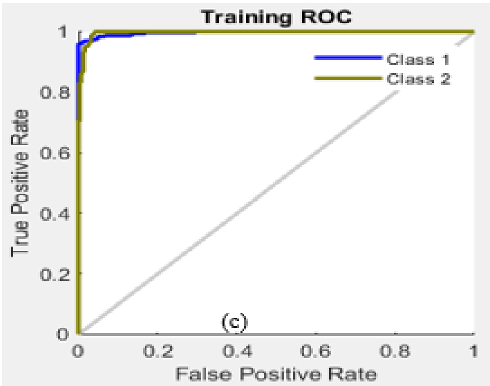
(a) (b)

Figure 8: a) Confusion Matrix for Classification Results (b) Training, Validation, Testing Confusion Matrix, and Overall Confusion Matrix

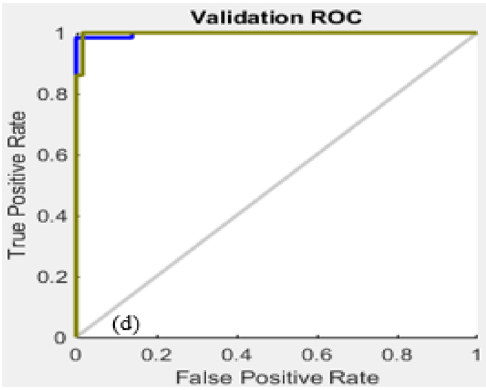
In table 3, analyzed the confusion matrix with different epochs then, we achieved the accuracy 99.71% with 15 epochs. So, this gives better accuracy than all other epochs. ROC is the Receiver operating characteristics, it can be plot with 22 epochs shown in Figure 10. The confusion matrix of the classification results is shown in the Table 2. The table shows the different performance measures such as precision, F1 score and accuracy. The table shows the proposed method achieved best accuracy in 15 epochs which is approximately 99%. Highest precision achieved is 98% and highest F1 score is also 98% approximately.

Table 2: Confusion Matrix Results of the Proposed Method

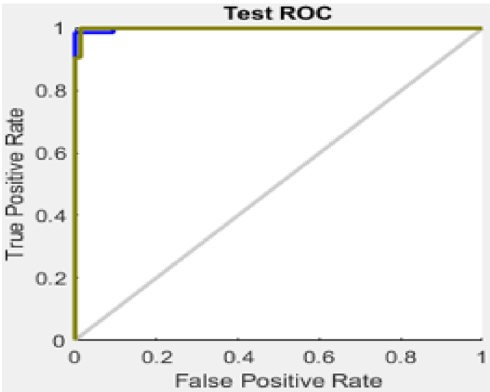
Experiment	Epochs	Precision	F1 score	Accuracy
1	5	0.9723	0.9734	0.9690
2	9	0.9759	0.9749	0.9671
3	11	0.9781	0.9770	0.9700
4	13	0.9623	0.9735	0.9823
5	15	0.9868	0.9825	0.9971
6	16	0.9845	0.9791	0.9728



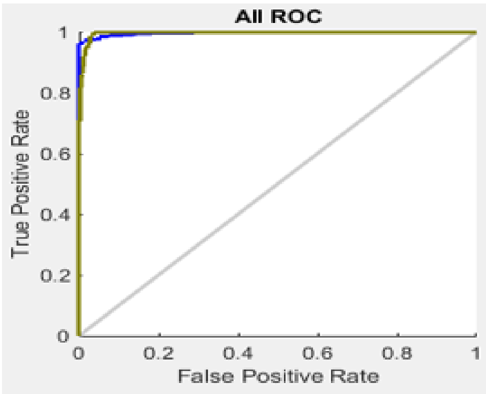
(a)



(b)



(c)



(d)

Figure 9: Neural Network Training Receiver Operator Characteristics ROC with 22 Epochs (a) Training ROC (b) Validation ROC (c) Test ROC (d) All ROC that plot ROC curves with respect to True Positive Rate and False Positive Rate

The result comparison of existing studies with proposed system that can be shown in Table 3. Table 4 depicts the results comparison from the existing methods, in which we observed that proposed model achieved competent performance as compared to latest existing works. Tools that are used for implementation of the proposed system.

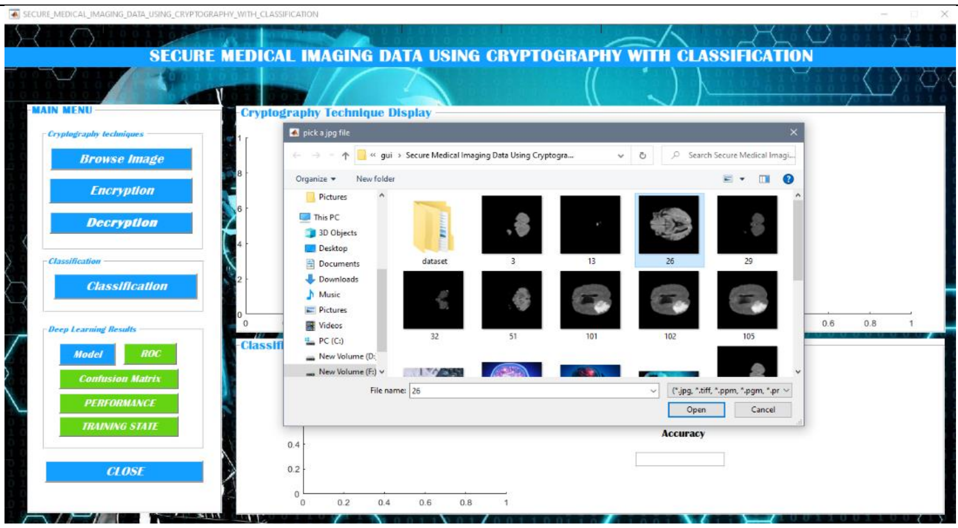
- MATLAB 2020a
- Intel Core i5 vPro 8th Gen
- Windows 11

Table 3: Comparison of Results with Existing and Proposed Methodology

Ref#	Year	Accuracy [%]
[22]	2023	98.00
[24]	2023	95.94
[25]	2023	98.9
[26]	2023	87.00
[27]	2019	84.19
[28]	2018	97.50
[29]	2015	96.15
[30]	2018	95.03
[31]	2019	92.61
[32]	2018	93.68
[33]	2021	90.0
Proposed System	2023	99.71%

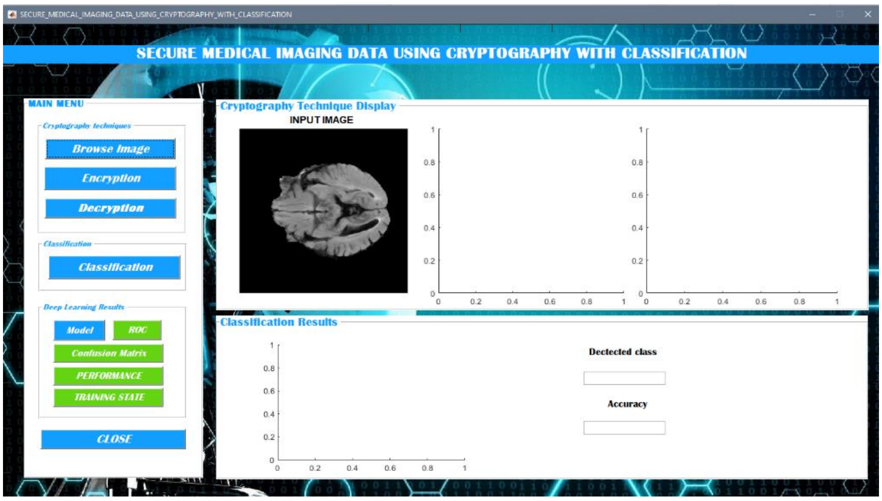
5. GRAPHICAL USER INTERFACE OF PROPOSED METHOD

Browse Image from dataset



(a)

Image browsed from dataset and show input image in axis1



(b)

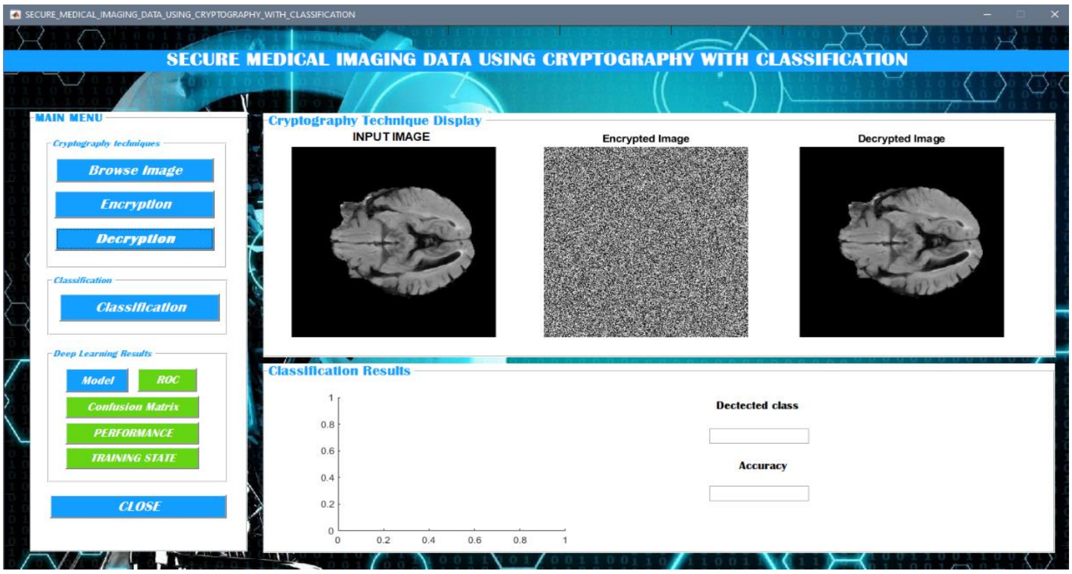
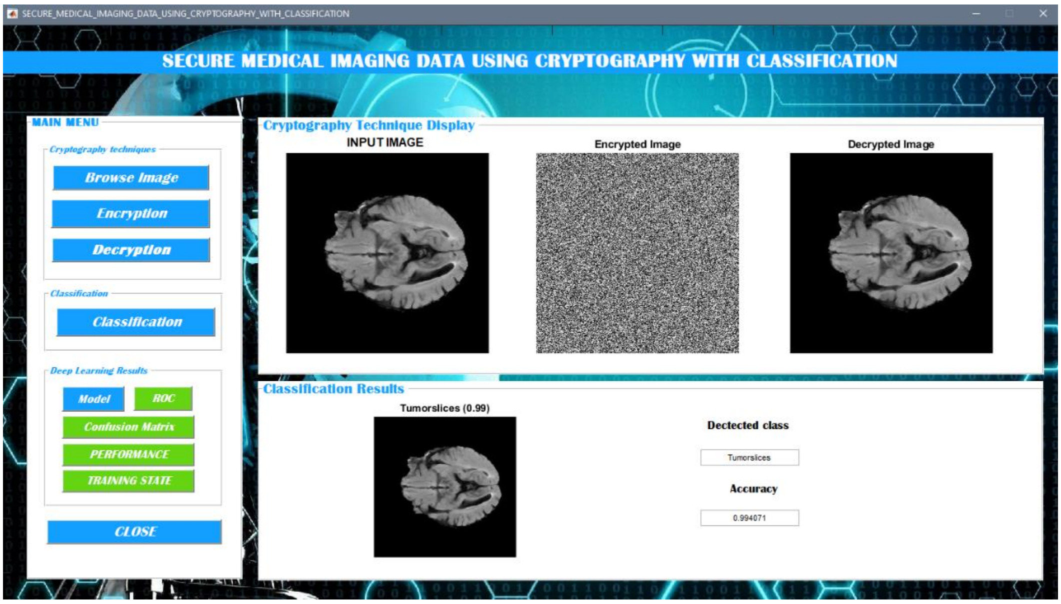
Encrypted image converted decrypted image	 (c)
Classification results	 (d)

Figure 10: (a) Browsing Image from Dataset (b) Browsed Image Show in Input Axis (c) Encrypted Image Converted into Decrypted Image (d) Classification Results

In Figure 10, desktop-based GUI is developed for real time classification of the brain tumor. In this application, firstly original MRI slices are passed to proposed methods steps such as encryption, decryption, features extraction and classification. (a) Browse image from dataset (b) browsed image show in input axis (c) Encrypted image converted decrypted image (d) Classification results shows that selected brain image at real time and it applies the cryptography, Advance Encryption Standard (AES), then detected class tumor slices and accuracy achieved up to 99.4%.

6. CONCLUSION

In this Research paper, an automated system to secure medical imaging data using cryptography and classification based on convolutional neural Network. The comprehensive experiments are conducted to evaluate the proposed method performance using BRAS-2020 Challenging dataset. The model comprises of the two core steps such as data security using public-key cryptography and classification based on the convolutional neural Network. The proposed model more accurately encrypts/decrypts the original images. Later decrypted images have been supplied as input to the pre-trained Alex-Network. The model achieved the training accuracy of 99.71%, validation accuracy of 97.17%, for classification between the tumor /non-tumor slices. The experimental results concluded that proposed model achieve the competitive results than recent published work. Proposed approach can be utilized in real-time applications to diagnose brain tumor at a premature stage. In future for the study of brain tumors using latest algorithms.

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