Rahimunnisa K, 2023, 11:2
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

Detecting Brain Tumors from MR Images Using Deep Transfer Learning-Based Models

Rahimunnisa K, Kaviya P, Paveethra K
Department of Electronics and CommunicationEngineering,
Easwari Engineering College,
Chennai, India
rahimunnisa.k@eec.srmrmp.edu.in, gheelosh21@gmail.com, pavilavan2001@gmail.com

Abstract- The treatment of seizures, peritumoral edema, adverse reactions to drugs, venous thromboembolism (VTE), weariness, and mental retardation are among the most prevalent medical issues in patients with brain tumors. There aren't numerous investigations that expressly tackle these areas of concern, considering how significant they are. A growing body of research shows that prophylactic antiepileptic drugs are ineffective in treating brain tumor patients who have not yet experienced a seizure. Due to a greater likelihood of contracting Pneumocystis jerovecii pneumonia, patients using corticosteroids may benefit from preventative medication. Additionally, there is increasing proof that suggests anticoagulation could be better compared with inferior vena cava (IVC) purification equipment during treatment of VTE in patients with brain tumors, because the possibility of bleeding from anticoagulation is comparatively low. Heparin with a low molecular weight might prove safer rather than Coumadin. The use of drugs like donepezil and memantine can be advantageous in treating cognitive impairment, whereas drugs like modafinil and methylphenidate have become more used for the management of weariness.

Keywords- venous thromboembolism, automatic computer- aided diagnostic (CAD) system, brain cancer investigation, and brain disease diagnosis and skin cancer image analysis.

I. INTRODUCTION

When unusual cells or tissues forms in the brain, a disease known as brain tumour result. According to the World Health Organization, 9.6 million people have received a cancer diagnosis globally. Early brain tumor diagnosis is among the key factors in saving the life of an individual. In order to accurately assess a patient's status, 65426 brain tumor images must be properly analyzed. Magnetic resonance (MR) scans are analyzed for abnormalities and choices are made by a physician or radiologist as part of the traditional procedure for finding brain tumors.

The degree of a physician's medical skill is crucial, though, as differences in expertise and the characteristics of the pictures make diagnosis with the unaided eye difficult. Given that they have a number of irregularities or inaccurate information, these images are difficult for a doctor to assess in a short amount of time. It becomes increasingly difficult to evaluate an immense quantity of data as its volume rises. A brain tumor's identification through observation becomes increasingly time and money-consuming. In order to aid physicians and radiologists in early identification of these fatal tumors and preserve valuable lives of individuals, an automatic computer-aided diagnostic (CAD) system is needed.

In order to find unusual brain abnormalities a brain tumour identification device often uses medical imaging methods like computed tomography (CT) or magnetic resonance imaging (MRI). Additionally, the system might examine the images to recognize probable tumors using machine learning methods.
The procedures for developing a system to identify brain tumors are as follows:

1. Gather and prepare data:
Gather information about brain imaging from numerous sources such as MRI or CT scans. The data should be pre-processed to make sure it is in a manner which is capable of being utilized for evaluation.

2. Feature extraction:
It is the process of removing characteristics from brain scan results. Form, dimensions, appearance, and placement of any anomalies in the images are only a few examples of these traits.

3. Training the model:
A machine learning model can be trained using the retrieved data. This might be a multiclass classifier that recognizes various tumor kinds or a binary classifier that differentiates between images with and without tumors.

4. Testing and validation:
To assess the model's effectiveness and precision, test it on a different dataset. To make sure the model applies successfully to fresh, untested data, it is crucial to complete this phase.

5. Deployment:
The model can be implemented as an application in software or incorporated into clinical imaging systems for immediate application after it has been successfully trained and verified.

- The propose system considers the development of novel architecture using deep transfer learning approach and Convolutional neural network (CNN).
- The input dataset images are collectively the MRI results of various patients.
- The goal of the system is to provide accurate classification for brain tumor images.

II. BACKGROUND STUDY

Ottom et al. It is difficult and important for the medical field to identify and divide brain tumours using MR imaging. Brain tumours should be identified and localized as soon as possible to allow doctors to choose successful therapy choices and possibly preserve lives. The ability, performance, and possibility of deep learning algorithms to aid in precise evaluation, prediction, and healthcare techniques have drawn the attention of researchers in medical imaging. By employing deep neural networks (DNN) and data augmentation techniques, this research proposes an innovative structure for categorizing 2D brain tumours in MRI scans. In order to spread the fundamental connections of a much smaller amount of effectively defined malignancies, such as numerous patients with low-grade glioma (LGG), to a number of many other fake instances, the suggested method (Znet) depends on the concepts of skip-connection, encoder- decoder designs, and data enhancement.

M. Ismail et al. According to the idea of tumour field effect, cancer is an underlying illness that has consequences far beyond the boundaries of the evident tumour. As a forceful brain tumour called glioblastoma (GBM), elevated pressure inside the skull brought on by the tumours load frequently results in brain ejection and poor prognoses. The study we are conducting depends on the theory that extremely aggressive tumours have an unbearable growth pattern that causes noticeable biomechanical tissue deformities in typical parenchyma, this, while mixed with regional morphological shifts in within the boundaries of the tumour on MRI scans, may completely record tumour field effect.

Our unified radiomic-Deformation and Textural Heterogeneity(r- DepTH) MRI-based classifier is presented particularly. Assessments of the minor changes in tissue distortions across adjacent typical parenchyma caused by the mass impact are included in this characterization. Diffeomorphic registration is used to non-rigidly coordinate with the patients' MRI images to a healthful template in this situation. The distortion area scales in the typical parenchyma are obtained with the reverse projection that results from it. The final result of training on Cohort 3 was C-indices of 0.75 and 0.63, HR and CI on Cohorts 1 and 2 of 24 (10 57) and 12 (6 21), respectively. According to our findings, the r-DepTH characterization could possibly be used as a thorough and reliable MRI-based anticipatory predictor for illness severity along with lifespan in solid malignancies.

A. Shah et al. The proliferation of unnatural brain cells results in a condition known as a brain tumour. Since tumours are rare and can take many different forms, it is challenging to estimate the likelihood of surviving of a patient who has been impacted. Magnetic Resonance Imaging (MRI) images can be used for recognizing these malignancies because they are crucial for pinpointing the location of the tumour; still identifying them manually is a labour-intensive and difficult process that may yield incorrect findings. To assist in addressing these limitations, computer-assisted methods must be employed. Deep learning (DL) models are being utilized in medical imaging for identifying brain tumours employing MR images as a result of developments in artificial intelligence (AI). In order to effectively categorize and diagnose brain tumour images, a deep convolutional neural network (CNN) EfficientNet-B0 base model is adjusted using the suggested levels in the present research.

To improve the appearance of the images, multiple adjustments are applied using image- enhancing processes. The findings demonstrate in which the suggested modified advanced EfficientNet-B0 exceeds various CNN algorithms through accomplishing the greatest degrees of classification precision, recall, and areas under curve values going faster than different modern designs, utilizing an average precision of 98.87% with regard to of recognition and identification. A comparison is conducted using several DL methods as VGG16, InceptionV3, Xception, ResNet50, and InceptionResNetV2.

S. Ahmad et al. In order to prevent serious illnesses that are incurable after a brain tumour has advanced, it is important to detect it earlier. An accurate identification of a brain tumour may be crucial for initiating the right therapy that ultimately decreases the individual's mortality proportion. Brain tumour diagnosis using 2D Magnetic Resonance (MR) pictures is now a common use of a deep learning-based categorization system. The recognition of brain tumours using a variety of deep learning techniques based on transfer learning has been examined in this paper.

On the basis of a set of labels that includes both normal- and abnormal-brain pictures, the research findings are presented. Seven techniques, including VGG-16, VGG-19, ResNet-50, InceptionResNetV2, InceptionV3, Xception, and DenseNet201, are employed for transfer learning. Five conventional classifiers—Support Vector Machine, Random Forest, Decision Tree, AdaBoost, and Gradient Boosting—follow every one of them. To assess the correct efficiency with regard to of reliability, precision, recall, F1-score, Cohen's kappa, AUC, Jaccard, and specificity, every configuration of deep learning-based extracted features and classifier are studied. The development curves for each of the pairings that had the best accuracy were then displayed. According to the data, the top model has a cross-validation ratio of 10 and a precision of 99.39%. It is anticipated that the findings in this study will be helpful in choosing the best deep transfer learning approach.

K.Hao et al. Brain tumours are a prevalent type of cancer that have an elevated fatality rate. For the purposes of surgical intervention and diagnosis in clinical settings, the automatic segmentation of brain tumours is important. Convolutional Neural Networks (CNNs) exhibit outstanding efficiency in processing images and visual analysis due to the growth of deep learning. Many CNN-based categorization designs, including FCN (Fully Convolutional Network) and Unet, have been suggested by scientists from the viewpoints regarding network layout, loss function, as well as attention function. The majority of them still are built on conventional pooling techniques like average pooling and maximum pooling, and that could result in an absence of distinctive or typical characteristics.

The tissues are typically relatively tiny, which makes characteristic dropping a greater challenge when categorizing brain tumours. In addition, since they can't adapt to changing data, static pooling methods like maximum and average pooling might not effectively capture the characteristics they possess in down sampling. In this article, we initially integrate maximum pooling and average pooling, after which we provide a unique generalized pooling (GP) procedure involving adjustable values. This marks an initial effort to further develop algorithms from the viewpoint of pooling procedures for the separation of brain tumours. According to the information from experiments, the generalized pooling approach beats conventional pooling methods in successfully categorizing tumors in the brain.

III. SYSTEM DESIGN

The automatic recognizing and categorizing of cancers of the brain is the subject of our investigation. MRI and CT scans are frequently used to examine the brain's physical structure. The paper attempts to recognize malignancies in brain MR images.

- The goal is to come up with an approach which ensures that there is evidence of a cancer through combining various methods in order to offer a reliable way of tumour identification in MR brain imaging.
- The primary objective of brain tumour diagnosis is to improve the diagnostic process. The techniques used include filtering, erosion, dilation, threshold, and tumour delineation techniques such as as identifying edges. This project's main goal is to remove tumours from MR brain scans and depict them in a way that is easier for anyone to comprehend.
- The goal of this effort is to present certain valuable knowledge for users in a more digestible style, particularly for the medical professionals attending to the patient.
- The purpose of this study is to describe an approach which can generate an image of the cancer that has been retrieved using an MR brain image.
- The final image is going to be able to demonstrate details about the tumor, such as its measurement, parameters, and location, as well as its border, which may be used to determine the best course of action in a variety of situations.
- By employing a convolution neural network, we can finally determine if the tumor is present in the provided MR brain image.
- The patient's therapy may be postponed by the current techniques' poorer accuracy and recollection stages, inadequate effectiveness, and longer processing times for image categorization. Recent investigations have employed deep learning to increase the efficacy of computer-aided medical diagnostics in the study of cancer of the brain. Magnetic resonance (MR) scans are analysed for abnormalities and choices are made by a physician or radiologist as part of the traditional procedure for finding brain tumours.

IV. METHODOLOGY

Recent investigations have employed deep learning to increase the efficiency of computer-aided medical diagnostics in the study of brain cancer. They are crucial to the medical field and serve as successful means of treating many serious illnesses, such as skin cancer evaluation and the identification of neurological conditions. For the categorization of brain cancers, DL techniques that utilize transfer learning and fine- tuning are favoured and frequently utilized. Deep convolutional neural networks, transfer learning, and fine- tuning will be used extensively in this study's comprehensive experimentation to streamline the categorization and finding of brain tumours.

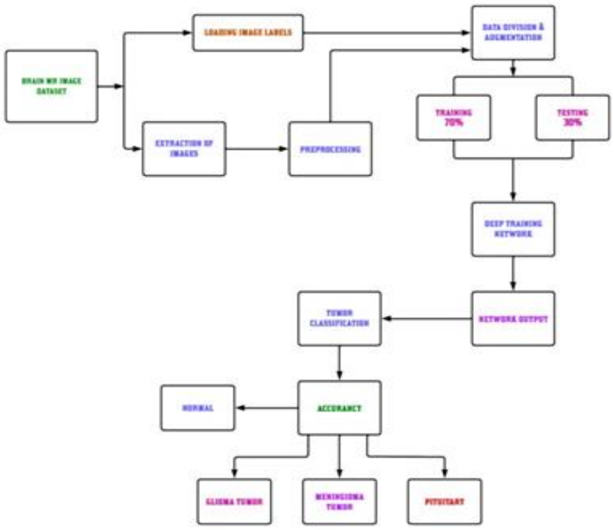

Fig 1. System architecture of Brain Tumor detection.

Fig 1. Shows the system architecture of proposed brain tumour detection system. The system read the image dataset, preprocess the images load the image labels into the workspace. Images are noise removed and data augmentation is processed.

- The proposed brain tumor classification system is implemented using deep transfer learning approach. The transfer learning is the method of continuous and iterative approach utilized to make the analysis model fit with the system to classify the patterns.
- Regardless of conventional pattern recognition system, the proposed deep iterative network performs with higher capability of feature correlation process.
- The novel system identifies the unique patterns present with the test data with respect to the training data using deep iterative transfer learning approach. The process read the unique features and continuously opted to save the pattern for further recognition process.
- The database images are split into 70% for training data, 30% for testing data.
- The initial process is carried out to fix the model that produce efficient classification result as well as better accuracy of prediction.

- The novel system is further tested with a part of the test data. the performance result is measured through degraded error rate and accuracy.

1. Proposed VGG16 architecture:

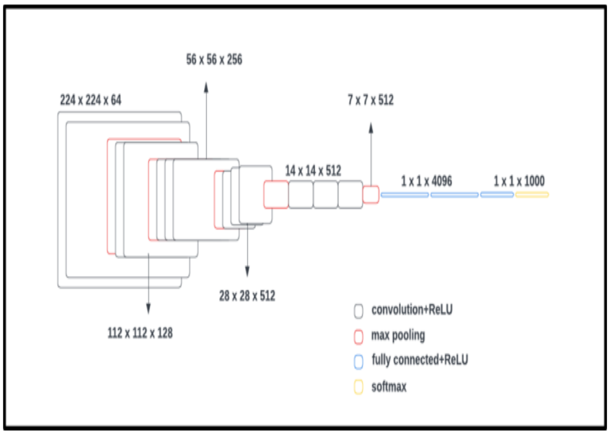

Fig 2. Proposed VGG 16 architecture

Fig 2. Shows the VGG16 architecture where the initial sizes of the input images are 224x224x3. The filtered images are 112x112x128 followed by the kernel filters of Max-pooling layer 56x56x256. The hybrid convolution layer with Max pooling layer of 28x28x512 dimension. Followed by the layer with filter size of 14x14x512. The final layer with 1x1x1000 is further processed.

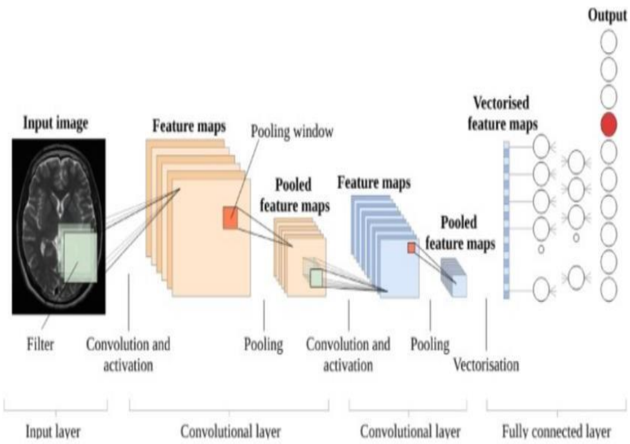

Fig 3. Proposed CNN architecture.

Fig 3. Shows the proposed CNN architecture with input layer, feature mapping layers, pooled feature maps, with convolution operation held at each stage. The vectorized feature maps are outputs of the each convolutional filter at every stage of the layers. The final outcome determines the highest correlated feature maps or intensity derived from the input block.

V. RESULTS AND DISCUSSIONS

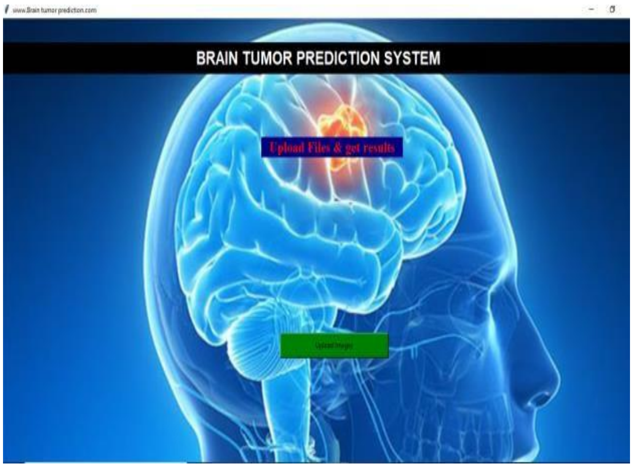

Fig 4. Image Upload page

Fig. 4. Shows the system results the web portal for image upload.

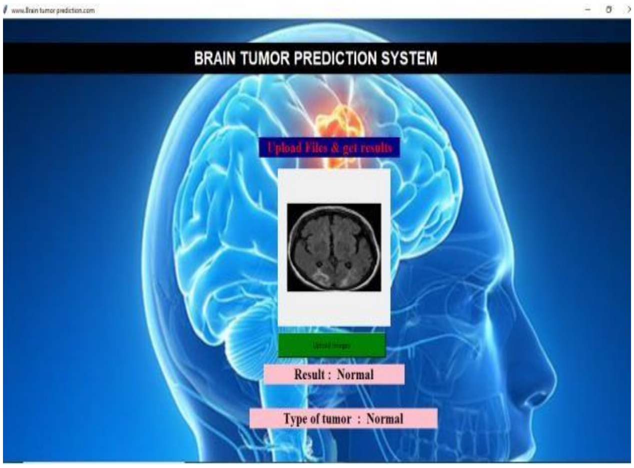

Fig 5. Normal class

Fig. 5. Shows the system resulting the Normal class after the deep transfer learning evaluation and verification.

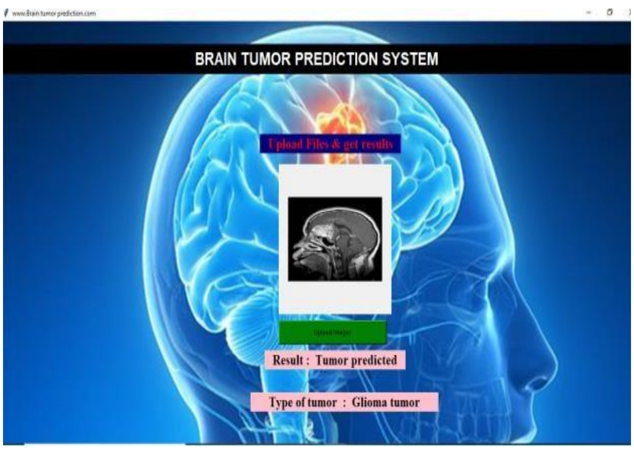

Fig 6. Glioma tumor class

Fig. 6. Shows the system resulting the detection of Glioma tumor class after the evaluation of deep transfer learning system.

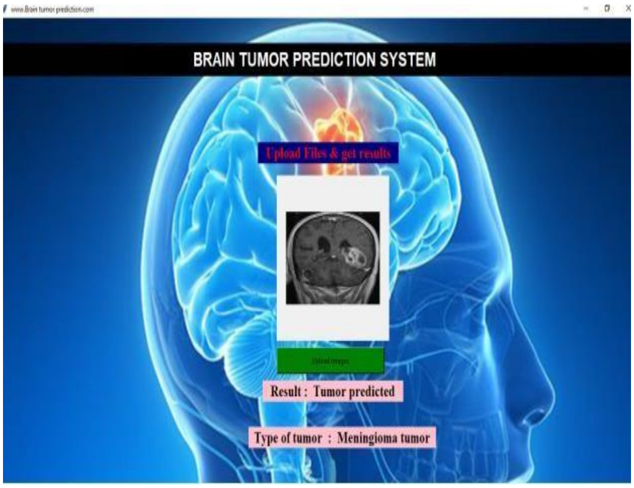

Fig 7. Meningioma Class

Fig. 7. Shows the system result showing the detection of Meningioma classification of tumor.

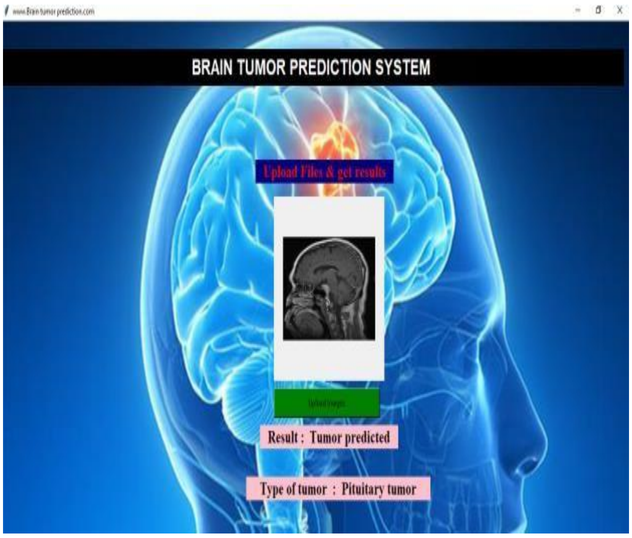

Fig 8. Pituitary tumor

Fig. 8. Shows the system resulting the detection of pituitary tumor.

The web page is utilized here to show the results in a customized way for the user to easily understand the detection process. Since the web application is configured the system can update the dynamic values into it. The major challenge persist with the system is handling large dataset and cloud occupation.

Fig 9. Comparison of CNN and TL in terms of accuracy is shown here.

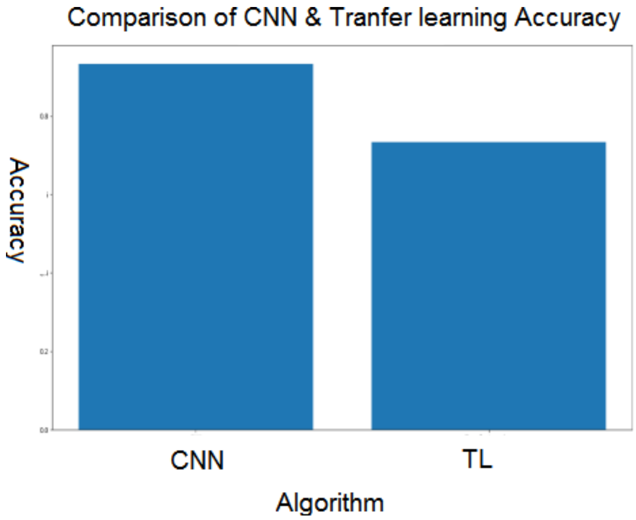

Fig 9. Comparison of CNN & TL accuracies

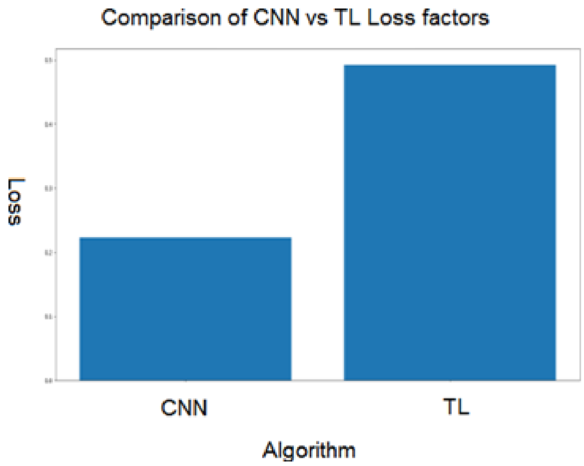

Fig 10. Comparison of CNN & TL Loss

Fig 10. Comparison of CNN and TL in terms of Loss factor is shown here.

VI. CONCLUSION

Due to the growing need for an efficient and reliable assessment of enormous quantities of healthcare information, MR imaging for determining the presence of brain tumours has become becoming more common. Manually recognizing brain tumours requires a great deal of time and medical knowledge, and it is a fatal illness.

It will be necessary to use an automatic diagnostic approach to find irregularities in MRI images. With an accuracy rating of 98.87%, the suggested method demonstrated the highest success rate in the identification of brain tumours. Additionally, in order to provide a foundation for future study, we will additionally be adapting the suggested method to various other clinical images like x-ray, computed tomography (CT), and ultrasound.

REFERENCES

[1] I. D. Dinov and M. V. Velev, Data Science: Time Complexity, Inferential Uncertainty, and Spacekime Analytics. Berlin, Germany: Walter de Gruyter, 2021.

[2] O. Hiwaki, ''Novel technique for noninvasive detection of localized dynamic brain signals by using transcranial static magnetic fields,' IEEE J. Transl. Eng. Health Med., vol. 9, pp. 1–6, 2021.

[3] R. Ranjbarzadeh, A. B. Kasgari, S. J. Ghoushchi, S. Anari, M. Naseri, and M. Bendechache, ''Brain tumor segmentation based on deep learning and an attention mechanism using MRI multi-modalities brain images,'' Sci. Rep., vol. 11, no. 1, pp. 1–17, Dec. 2021.

[4] M. U. Rehman, S. Cho, J. H. Kim, and K. T. Chong, ''BU-Net: Brain tumor segmentation using modified U-Net architecture,'' Electronics, vol. 9, no. 12, p. 2203, Dec. 2020.

[5] S. Ghosh, N. Das, I. Das, and U. Maulik, ''Understanding deep learning techniques for image segmentation,'' ACM Comput. Surv., vol. 52, no. 4, pp. 1–35, Jul. 2020.

[6] M. Rashed-Al-Mahfuz, M. A. Moni, S. Uddin, S. A. Alyami, M. A. Summers, and V. Eapen, ''A deep convolutional neural network method to detect seizures and characteristic frequencies using epileptic electroencephalogram (EEG) data,'' IEEE J. Transl. Eng. Health Med., vol. 9, pp. 1–12, 2021.

[7] A. Saha, Y.-D. Zhang, and S. C. Satapathy, ''Brain tumour segmentation with a muti-pathway ResNet based UNet,'' J. Grid Comput., vol. 19, no. 4, pp. 1–10, Dec. 2021

[8] M. A. Ottom and K. M. Nahar, ''Computer aided diagnosis for chronic kidney disease using data mining,'' Int. J. Cyber-Secur. Digit. Forensics, vol. 8, no. 3, pp. 188–194, 2019

[9] Y. Al-Issa, M. A. Ottom, and A. Tamrawi, ''eHealth cloud security challenges: A survey,'' J. Healthcare Eng., vol. 2019, pp. 1–15, Sep. 2019.

[10] N. E. Khalifa, M. Loey, and S. Mirjalili, ''A comprehensive survey of recent trends in deep learning for digital images augmentation,'' Artif. Intell. Rev., vol. 55, pp. 2351–2377, Mar. 2022.