International Journal of Engineering Technology and Management Sciences
Website: ijetms.in Issue: 5 Volume No.6 Aug-Sept – 2022
DOI:10.46647/ijetms.2022.v06i05.112 ISSN: 2581-4621

A Web Based e-health Care Application for Brain Tumor Detection and Analysis

Aswani. K[1], Dr.D.Menaka[2]
[1]*Research Scholar, NICHE University, Kumarankoil, Tamilnadu*
[2]*Associate Professor, Electronics and Instrumentation, NICHE University, Kumarankoil, Tamilnadu*

ABSTRACT
One of the most serious health issues in today's world is cancer. It may affect different parts of the body and will be identified only in the last stages. One of such cancers is brain tumor. The uncontrollable growth of tissues in the brain causes tumors, which reduces the life span of the affected person. The current treatment method is based on the biopsy procedure. The medical persons may decide different treatment procedures based on the biopsy report. The success of these treatments in most cases depends on how early it can diagnose the tumor and start the medical procedures. Here the authors propose an intelligent e-health application which will help people with early detection of tumors. The author's application is web based and makes use of the possibilities offered by Internet of Medical Things (IoMT). People with internet access can login to the application and upload the MRI scan for diagnosis. The tumor detection and segmentation procedure are based on deep learning. Another advantage of the proposed model is its periodic updating capabilities. All the models will be periodically updated to provide the best results possible. The uploaded data will be used for training the model only with the consent of the people responsible. The authors hope this platform will give a new dimension of services towards e-healthcare services that improve the quality of medical services.
Key Words: IoMT, Brain Tumor, Low Code, AutoML

1. Introduction

The Internet of things (IoT) is now often utilised for a wide range of purposes, and its importance in our day-to-day lives is increasing significantly. IoT innovation also the healthcare system is changing to offer patients services that are efficient [1]. As one of the most difficult medical conditions, brain tumour demands special treatment. The kind of the tumour must be accurately and promptly diagnosed before a brain tumour may be classified. Since the choice of effective treatment modalities mostly depends on the pathological kind. However, the traditional method for identifying and categorising magnetic resonance imaging (MRI) brain cancers relies mainly on human observation and the knowledge of radiologists who research and practise radiology and interpret image. Characteristics and usually give a non-accurate diagnosis. Computer-aided diagnostic methods are highly desirable for these issues [2].
An unwelcome collection of abnormal brain cells is known as a brain tumour. Noncancerous and malignant brain tumours are the two different sorts [3]. Noncancerous (benign) tumours develop more slowly than malignant tumours and do not invade nearby tissue or organs [4]. Additionally, there are two categories of cancerous tumours (malignant): primary tumours that begin inside the brain and secondary tumours known as brain metastasis tumours that spread from other places. Accurate and prompt grade detection of brain tumours has a significant impact on patient treatment choices as well as tumour growth assessment and early stage brain tumour diagnosis. Due to the variations in the size, shape, contrast, and location of tumour cells, classifying tumours is one of the most difficult tasks. To distinguish between benign and malignant tumours, tumours are categorised according to their grade, which runs from I to IV. The diagnosis and treatment of diseases depend significantly on the use of medical images such as X-rays, computed tomography (CT), MRI, and ultrasound. The most frequently used diagnostic and evaluation techniques for brain tumours are CT

and MRI. Due to its superior level of resolution, MRI is regarded as the primary modality, particularly for brain imaging [5].

2. Existing methods.

The earliest possible detection of a brain tumour is crucial for the implementation of effective treatment, making it the most significant factor in brain tumour disease. Based on this information, the best course of treatment—whether radiation, surgery, or hemotherapy—can be chosen. As a result, if the tumour is adequately identified in its early stages, the patient's chances of survival can be significantly increased. As shown in Table 1, numerous researchers have described various techniques for identifying tumour regions in MRI scans based on conventional ML and DL procedures. In addition to a binary classification for high and low grades, Zacharaki et al. [6] proposed a technique to identify various grades of glioma using support vector machines (SVMs) and K-nearest neighbours (KNN). The accuracy of binary classification is 88 percent, compared to 85 percent for multi-classification. By expanding the tumour area through picture dilatation and then splitting it into subspaces, Cheng et al. developed a method to improve brain tumour identification performance [7]. By combining ring form splitting and tumour region expansion, they were able to achieve the highest accuracy of 91.28 percent. Brain MRIs were categorised by Shree and Kumar in [8] as normal or abnormal, they used GLCM to extract features, while a probabilistic neural network (PNN) classifier was used to classify the brain MR image and achieved 95% accuracy. For all computing applications, deep learning techniques have increased in importance among artificial intelligence methods. For any practical application, deep convolutional neural networks (DCNNs) are one of the most often used deep learning networks. The accuracy is typically very high, and these networks do not need to use the human feature extraction method. However, excellent accuracy comes at a considerable computational expense. Researchers employed various CNN models such as Google Net, Inception V3, DenseNet-201, Alex Net, and ResNet-50 and obtained good accuracies.

M. K. AbdEllah et al. created the Deep CNN architecture to find brain cancers in MRI images [9]. By creating a new CNN architecture, they improved their model and achieved an accuracy of 97.79%. In order to extract features from brain MR images and classify three different types of brain cancers with 98 percent accuracy, Deepak and Ameer [10] used deep CNN and a pre-trained Google Net. Saxena et al. in [11] used transfer learning techniques using Inception V3, ResNet-50, and VGG-16 models. The best accuracy rate, 95%, was reached by the ResNet-50 model. A modified DCNN was utilised by Hemanth et al. [12]. The traditional DCNN's completely connected layer underwent modification. They then used an allocation process to determine the weights in the fully connected layer. By removing the final five layers of a pre-trained ResNet-50 CNN and replacing them with eight new ones, researchers were able to improve the model's accuracy to 97.2 percent [13]. A CNN model was recommended by Khwaldeh et al. [14] for distinguishing high-grade and low-grade glioma tumours as well as brain MR images. They achieved 91 percent accuracy by modifying the Alex Net CNN model and using it as the basis for their network architecture. The accuracy for classifying MRI images with and without tumours using transfer learning for several variation CNN architectures was 92%, 91%, and 88% for MobileNetV2, InceptionV3, and VGG19, respectively, according to the authors of [15].

In conclusion, the research above demonstrates that the accuracy attained by employing deep learning with CNN network design to classify brain MRI is significantly higher than that obtained by using outdated conventional methodologies. In contrast, deep learning models need a huge amount of data to train in order to perform better than standard machine learning methods.

3. IoMT System Model

The IoT system on which our model is built sends brain images to the cloud for classification as seen in Fig. 1 in order to function. This architecture is regarded as a multiuser access system, allowing numerous users to connect to the cloud simultaneously. There is only one common

DOI:10.46647/ijetms.2022.v06i05.112 ISSN: 2581-4621

receiver shared by all users. An IoT system with cloud administration was created to classify brain tumours.

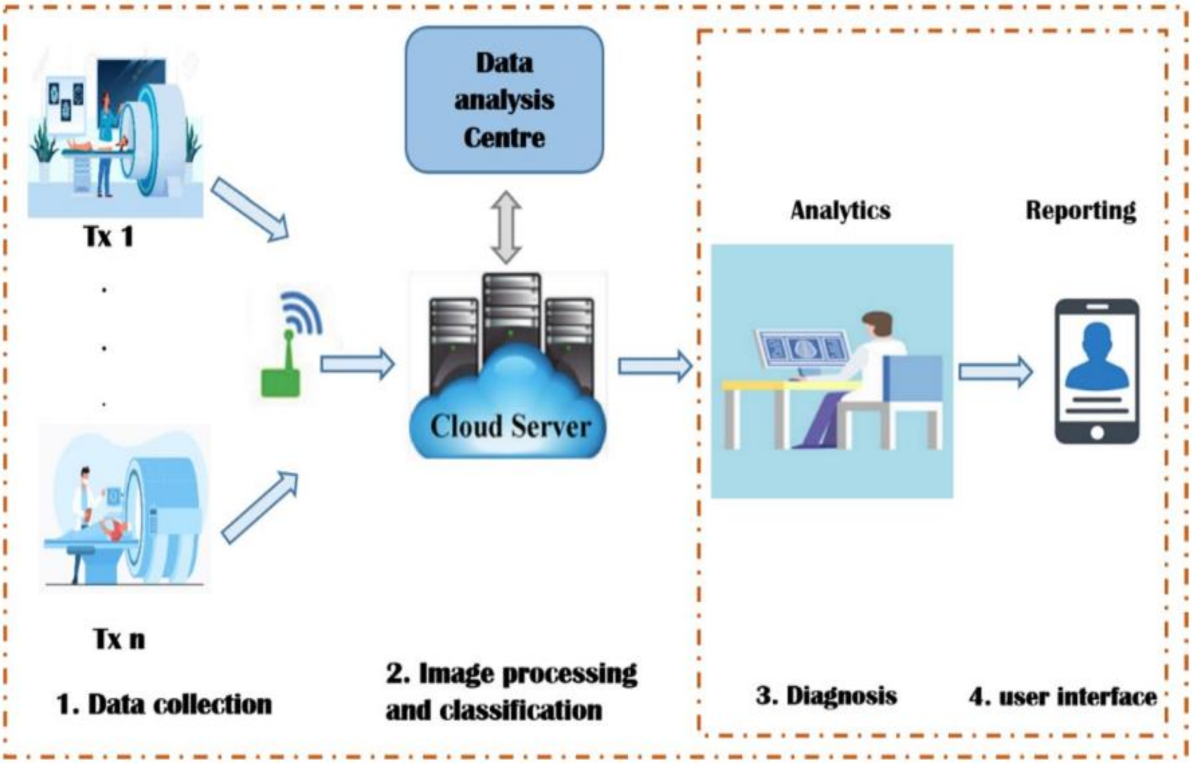

Fig.1. IoMT System Architecture

The cloud is the greatest answer for a medical system that allows doctors to access data more readily because it is a dispersed environment. Our suggested IoT framework comprises four primary phases: data collecting, image processing and classification, diagnosis, and user interface. Its goal is to lower mortality rates through early detection of malignant malignancies.

The suggested IoT system is an integrated system that begins by using MRI equipment to gather brain images throughout the data collection phase. The MRI images are then scaled to fit the suggested CNN model (OMRES), which extracts features from the processed images and employs a SoftMax classifier to detect brain tumours, before being transmitted via the WIFI module to the cloud for preprocessing and classification. The patient can access his database to find the classification results during the analytics phase. By uploading an MRI and receiving classification results in just a few seconds, a radiologist can identify a tumour type (if there is one) in a matter of seconds. The patient's doctor receives the report at the last phase, and he or she will determine the best course of action. The system is made up of a transmitter and a receiver for each user. The transmitter is in charge of getting the patient's scanned image ready for transmission over the wire, and the receiver is in charge of decoding the image after it has been received and extracting the features needed for the early identification of brain tumours.

High-quality images are first created at the transmitter by scanning the patient's brain using a magnetic field and computer-generated radio waves. It is then transformed into binary data and sent over the air. The patient Identifer (ID) is then included as a header to the binary data vector, which is formed after that. Following that, convolutional codes with a code rate of 23 are used to encrypt the data frame before it is broadcast.

As seen below, we can define the coding rate r.

$$r = \frac{k}{n}$$

where n is the number of parallel output encoded bits at a single time period and k is the number of parallel input bits. Fig. 5 depicts the transmitter part's data flow.

International Journal of Engineering Technology and Management Sciences
Website: ijetms.in Issue: 5 Volume No.6 Aug-Sept – 2022
DOI:10.46647/ijetms.2022.v06i05.112 ISSN: 2581-4621

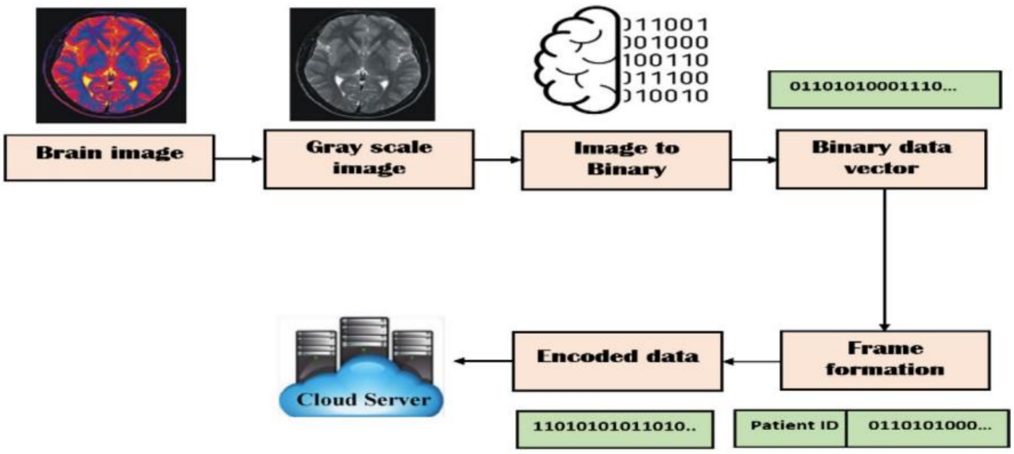

Fig.2. Dataflow of the prposed IoMT system

The "Registration mode" and the "Operation mode" are the two operating modes at the receiver, as depicted in Fig. 3.

Mode of Registration Any new user just needs to use the registration mode once. When a patient first registers, their ID number is given to them so they can readily access their account in the system. Operating Style The authentication mechanism is initially used in this mode to identify the registered user. Following that, image preparation is carried out to get the picture ready for the following steps. To cut down on noise, use the Weiner filter. The scaled data is then applied to the specified CNN model, in feet. The SoftMax classifier is then utilised to detect brain tumours after the suggested CNN model extracts features from the processed pictures. The patient can finally use his or her database to locate the classification outcomes.

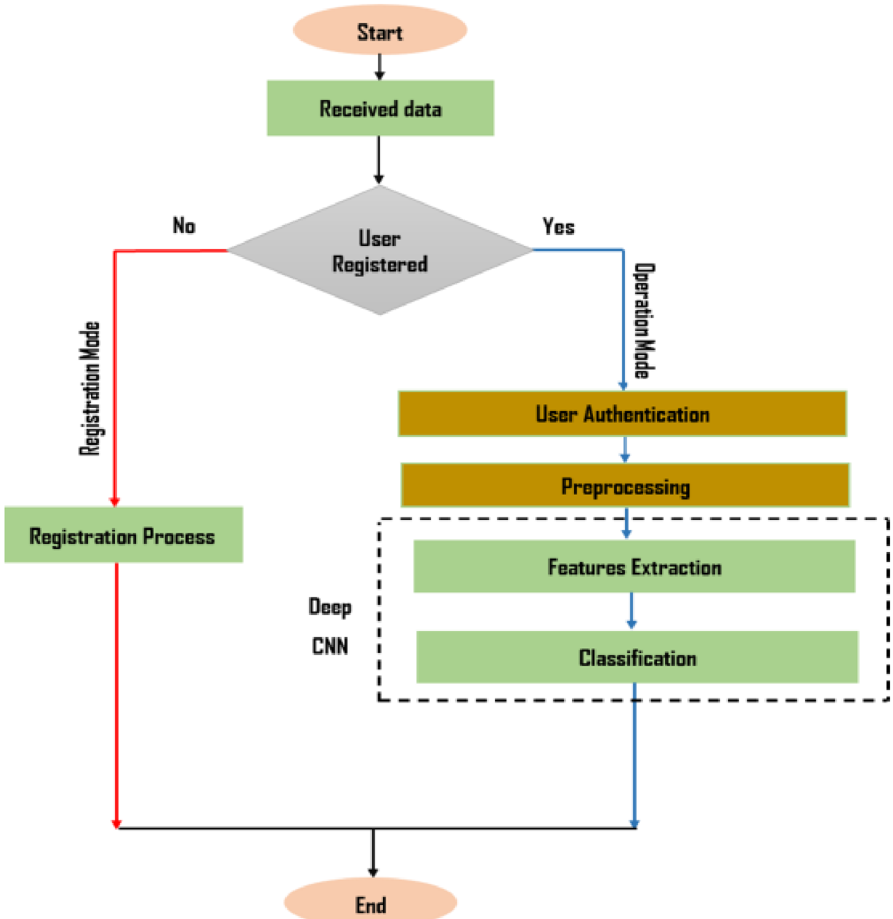

Fig.3. Flowchart of data receiving part.

International Journal of Engineering Technology and Management Sciences
Website: ijetms.in Issue: 5 Volume No.6 Aug-Sept – 2022
DOI:10.46647/ijetms.2022.v06i05.112 ISSN: 2581-4621

4. Discussion

The first scenario is predicated on the patient being present in the same location as the data centre, where a direct diagnosis of images is done by applying the images directly to the DCNN. This section describes two distinct ways for the early detection of brain cancers. The second concept involves uploading brain scans to a cloud-based data centre where tumour cells can be found. As illustrated in Fig. 4, this scenario enables several users to diagnose their images from anywhere in the same city.

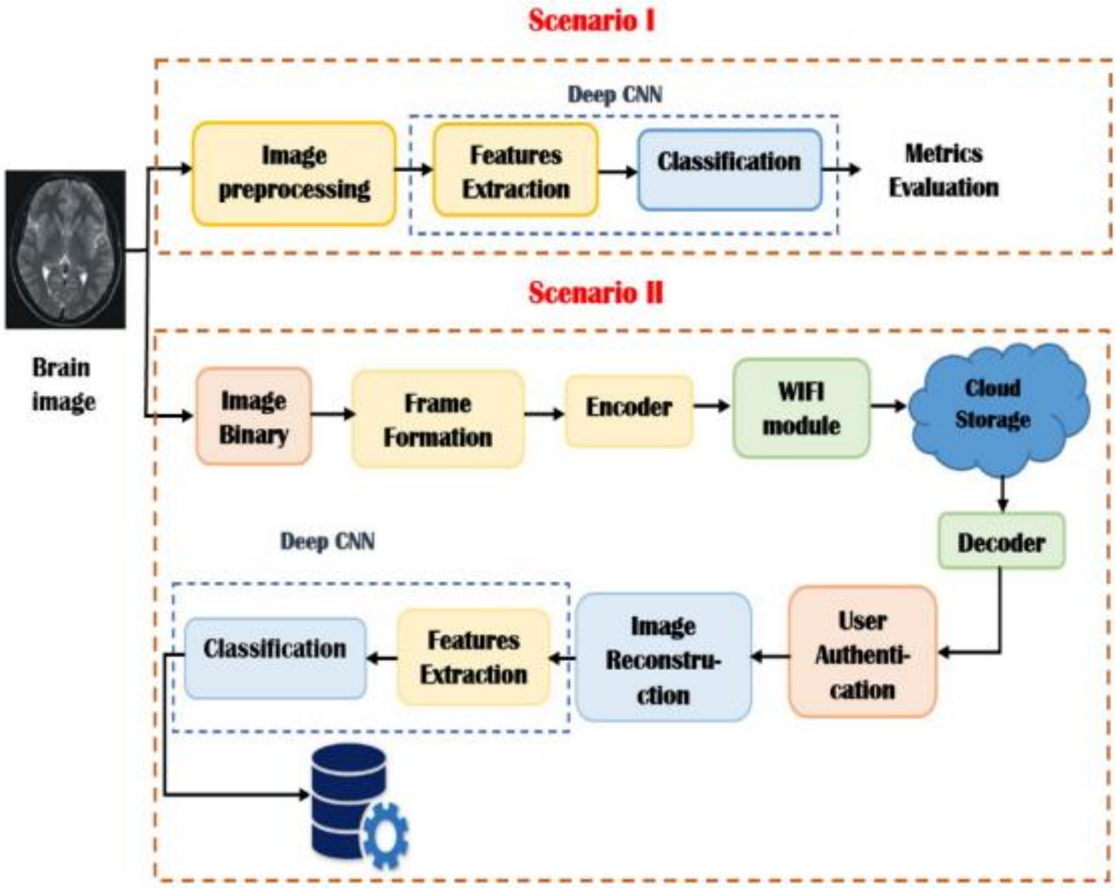

Fig.4. Direct method and proposed method comparison

Scenario I base on picture feature extraction on deep CNN. To ensure that all of the photos in the dataset have the same size before being placed into CNN, the image is first loaded and shrunk to 224x224 pixels. This is because the majority of brain datasets have images of varied sizes. Preprocessing then improves the image quality of brain tumour MR pictures and gets them ready for further examination by clinical professionals or other imaging modalities. It also helps to improve the qualities of MR images. Among the crucial factors in the image preparation process are enhancing the signal-to-noise ratio and visual look of MR images, eliminating unnecessary noise and background areas, smoothing internal part areas, and maintaining pertinent borders. Then, feature extraction is the process of extracting quantitative information from an image, such as colour characteristics, texture, shape, and contrast. Here, CNNs are used to execute the deep feature extraction procedure. The classification algorithm then uses the final feature descriptor to decide whether the input image is normal or abnormal. The fully connected layer transforms the input data into a 1D vector. The class scores are then calculated by the SoftMax layer.
The brain images in Scenario II are sent to the cloud to be classified, as shown in Fig. 3, using an IoT system. This architecture is regarded as a multiuser access system, allowing numerous users to connect to the cloud simultaneously. There is only one common receiver shared by all users. An IoT system with cloud administration was created to classify brain tumours. Because it is a distributed environment, the cloud is the best solution for a medical system that enables doctors to access data

more easily. Our suggested IoT framework comprises four primary phases: data collecting, image processing and classification, diagnosis, and user interface. Its goal is to lower mortality rates through early detection of malignant malignancies.

CONCLUSION

Here we propose a cloud based IoMT architecture for brain tumor detection. The advantage of the proposed method over the existing deep learning techniques is its user accessibility, continuous updating capability and reliability. The user can chose a wide range of models training the data. The authors hope this platform will give a new dimension of services towards e-healthcare services that improve the quality of medical services.

References.

1. Mohammadi M et al (2018) Deep learning for IoT big data and streaming analytics: a survey. IEEE Commun Surv Tutor 20:2923–2960. https://doi.org/10.1109/COMST.2018.2844341
2. Abbas S, Mahmoud AM (2020) Deep learning-aided brain tumor detection: an initial experience based cloud framework. Indones J Electr Eng Inform (IJEEI) 8:770–780. https://doi.org/10.52549/ijeei.v8i4.2436
3. Kapoor L, Thakur S (2017) A survey on brain tumor detection using image processing techniques. In: 7th International Conference on Cloud Computing, Data Science & EngineeringConfuence, pp 582–585. https://doi.org/10.1109/CONFLUENCE.2017.7943218
4. Kothari A, Indira B (2015) A study on classification and detection of brain tumor techniques. Int J Comput Eng Technol 6(11):30–35. https://doi.org/10.1007/s13735-020-00199-7
5. Goel N, Yadav A, Singh BM (2016) Medical image processing: a review. In: Second International Innovative Applications of Computational Intelligence on Power, Energy and Controls with their Impact on Humanity (CIPECH), pp 57–62. https://doi.org/10.1109/CIPECH.2016.7918737
6. Zacharaki E, Wang S, Chawla S, Soo Yoo D, Wolf R, Melhem E, Davatzikos C (2009) Classifcation of brain tumor type and grade using MRI texture and shape in a machine learning scheme. Magn Reson Med 62(6):1609–1618. https://doi.org/10.1002/mrm.22147
7. Cheng J, Huang W, Cao S, Yang R, Yang W, Yun Z, Wang Z, Feng Q (2015) Correction: enhanced performance of brain tumor classifcation via tumor region augmentation and partition. PLoS ONE 10(12):e0144479. https://doi.org/10.1371/journal.pone.0140381
8. Shree NV, Kumar TNR (2018) Identifcation and classifcation of brain tumor MRI images with feature extraction using DWT and probabilistic neural network. Brain Inform 5:23–30. https://doi.org/ 10.1007/s40708-017-0075-5
9. Abd-Ellah M, Awad AI, Khalaf AAM, Hamed H (2020) Deep convolutional neural networks: foundations and applications in medical imaging. pp 233–260. https://doi.org/10.1201/9781351003827-9
10. Deepak S, Ameer PM (2019) Brain tumor classifcation using deep CNN features via transfer learning. Comput Biol Med 111:103345. https://doi.org/10.1016/j.compbiomed.2019.103345
11. Saxena P, Maheshwari A, Maheshwari S (2019) Predictive modelling of brain tumor: A deep learning approach. arXiv 2019, arXiv:1911.02265. https://doi.org/10.1007/978-981-15-6067-5_30
12. Hemanth DJ, Anitha J, Naaji A, Geman O, Popescu DE (2018) A modified deep convolutional neural network for abnormal brain image classification. IEEE Access 7:4275–4283. https://doi.org/10. 1109/ACCESS.2018.2885639
13. Çinar A, Yildirim M (2020) Detection of tumors on brain MRI images using the hybrid convolutional neural network architecture. Med Hypotheses. https://doi.org/10.1016/j.mehy.2020.109684
14. Khawaldeh S et al (2017) Noninvasive grading of glioma tumor using magnetic resonance imaging with convolutional neural networks. Appl Sci. https://doi.org/10.3390/app8010027

DOI:10.46647/ijetms.2022.v06i05.112 ISSN: 2581-4621

15. Tazin T, Sarker S, Gupta P (2021) A robust and novel approach for brain tumor classifcation using convolutional neural network. Comput Intell Neurosci. https://doi.org/10.1155/2021/2392395