BRAIN TUMOR DETECTION AND LOCALIZATION USING Faster RCNN

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Abstract:

A brain tumour is an abnormal and uncontrolled growth of cells that begins in the brain. Damage to critical tissue and pressure on the brain brought on by the tumour's growth within the skull's constrained area are two common causes of brain tumour symptoms. Therefore, it poses a serious risk to the human brain, and the prognosis of brain tumours can be greatly influenced by early detection. As is commonly known, manual detection of brain tumours takes the time required for diagnosing a brain tumour depending on the clinician's knowledge and experience levels.

The existing technique uses a convolution neural network (CNN) to find the brain tumour's popular artificial neural network for image processing is the convolution neural network (CNN). It begins by taking the input image from an MRI scan and then uses Enhancing images by applying various filters to improve their quality is a common practice in image processing. Data augmentation techniques are commonly employed to expand the dataset for training a model, one can increase the number of data samples. Once the training is finished, the model's output typically consists of two categories: a tumour image and a non-tumour image. Yet, it's worth noting that this approach has a limitation as it can only ascertain the presence or absence of a tumour from the image; it cannot precisely identify the tumour within the image.

The proposed method employs an effective algorithm to precisely determine the location of the tumour within the image. R-CNN, a deep learning technique, and the deep convolution neural network are used in this algorithm.

KEYWORDS: Brain tumour detection, deep learning, MRI, Region with convolution neural network, brain tumour detection and localization techniques.

1. INTRODUCTION

The brain is the most complex and vital part of the human anatomy, containing structures and nerve cells that regulate crucial processes of the entire body such as breathing and the operation of our senses and muscles. A cell has capabilities; with their functioning, some cells develop properly, while others diminish their capabilities, cease growing, and then become abnormal. The tissue known as a tumour is formed by a large group of irregular cells. Brain tumours are thus the result of the autonomous and irregular proliferation of brain cells. Brain tumours are a leading cause of death and disability worldwide because they affect the most essential organ in the human body.

A brain tumour develops when abnormal cells within the body undergo uncontrolled proliferation. Brain tumours are typically classified into two main categories: malignant (cancerous) and benign (non-cancerous). Malignant or cancerous tumours are further divided into primary tumours, which originate within the brain, and secondary tumours, which have metastasized to the brain from elsewhere in the body. All types of brain tumours can manifest a range of symptoms that vary depending on the specific area of the brain they affect. Possible symptoms include headaches, seizures, vision problems, vomiting, and cognitive abnormalities.

A variety of brain tumour types exist, including benign, malignant, and pre-malignant forms. Malignant tumours can be further classified into two main groups: primary tumours, which originate within the brain, and secondary tumours, which are tumours that have spread to the brain from other parts of the body, known as brain metastasis tumours.

1.1 Brain Tumour Classification

Tumours are classified into three types: 1) benign tumour 2) Pre-cancerous 3) Cancer (cancer is exclusively malignant).

A. Benign tumour:

A benign tumour is a non-malignant or non-cancerous growth. Unlike cancer, it does not often infect surrounding tissues or spread to other sections of the body. Benign tumours generally have a favourable prognosis, but they can pose a threat if they exert pressure on vital structures such as blood vessels or nerves.

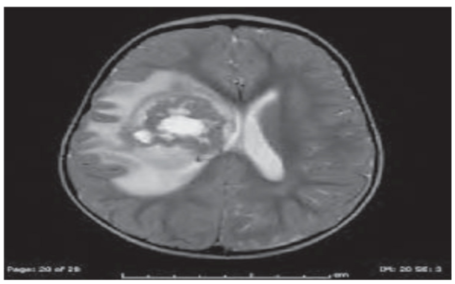

Fig 1: Benign Tumour

B. Pre-cancerous tumour

The cells within benign tumours are not malignant, but they may possess the potential to transform into cancerous cells. These cells will develop and differentiate into various components of the body.

C. Cancerous tumour

Malignancy (from the Latin words mal ("bad") and ignis ("fire") Cancerous tumours are malignant tumours. Malignant tumours form when cells undergo uncontrolled growth. The condition can become life-threatening if these cells persist in their development and proliferation. Malignant tumours develop quickly and can spread to other parts of the body.

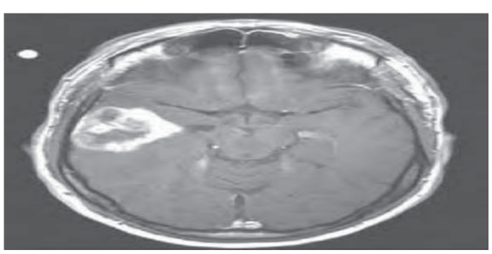

Fig 2: Malignant Tumour

A tumour is essentially an uncontrolled proliferation of cells. In the case of brain tumours, these cells grow in a manner that can eventually deplete the nutrients meant for healthy cells and tissues, potentially leading to brain dysfunction. Currently, professionals manually identify the exact position and size of a brain tumour by reviewing the patient's MRI scans of the brain. This method can lead to inaccuracies in tumour detection and is considered time-consuming.

Medical professionals employ several imaging techniques to detect brain tumours, including Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), and Computed Tomography (CT). When comparing these imaging modalities, MRI is often regarded as the most effective in detecting brain tumours.

Initial identification of brain tumours may drastically improve alternatives to therapy and patient survival rates. However, manually classifying tumours utilizing an immense amount of magnetic resonance imaging (MRI) images from surgical procedures is a tedious and laborious operation. Magnetic resonance imaging (MRI) scans are important in computerized medical evaluation since they allow for the recognition of distinct neural connections as well as particular details regarding each. Several ways for diagnosing and categorizing brain tumours have been tried using MRI scans. Currently, brain tumours are only diagnosed. Even those individuals are considered to be at risk due to their genetic composition for specific types of brain tumours, and there are no early detection tools in place. Many ML algorithms were employed to detect brain tumours, many of which are supervised methods. Numerous studies have been undertaken to investigate why the system fails owing to coefficient overhead, overfitting, and less effective feature extraction. A deep learning method does not optimize the selection of several layers in the learning and classification system.

This study focuses on a system that utilizes computer-based processes to identify tumour regions and localize tumours within MRI scans of various patients through a regional Convolutional Neural Network (CNN) algorithm. Image processing techniques, including image augmentation, image data processing, and training models, are employed to detect brain tumours in MRI scans of cancer patients. The process of brain tumour detection using image processing techniques comprises four phases: image pre-processing, image augmentation, model training, and detection and localization. Image processing and CNN techniques are harnessed to enhance the performance of brain tumour detection and localization in MRI images.

In our research paper, our proposed RCNN-based algorithm, with an accuracy of 99.13%, is aimed at assisting medical professionals in their treatment efforts by eliminating the need for manual analysis of MRI images. This would potentially expedite treatment processes.

1.2 Deep Learning-Based Techniques for Detecting Brain Tumours:

Deep learning refers to a sort of training-based AI technology model with multiple layers to create hierarchical representations of data. This approach has advanced various fields, including speech recognition, object recognition, and many others. Training in deep learning can be supervised or unsupervised. Deep learning transforms raw input data at each level into increasingly abstract and structured representations. In a tumour recognition application, the initial layer might abstract pixel information and encode tumour edges, while subsequent layers may encode arrangements of tumour edges and representations of shapes, ultimately identifying the presence of a tumour within an image. Essentially, deep learning processes autonomously learn to identify and position features accurately.

2. EXISTING SYSTEM

The CNN model, which stands for Convolutional Neural Network, underpins the technique. The layer of convolution, the layer for pooling, & the layer that is fully connected are the three core layers of deep learning. CNNs have many layers of convolution and a layer for pooling, which is frequently followed by several fully linked layers.

A. Convolution layer: The layer of convolution is the first layer, and it serves to obtain characteristics of the image being processed. The process of convolution is performed over the picture and the selected MxM filter in this layer. This procedure produces a feature map, which transmits details about the appearance including features that include edges and corners.

B. Max Pooling layer: The major goal of this type of layer was to decrease the dimension of the convoluted feature map, which aids in the reduction of computing expenses. The pooling layer essentially summarizes the features obtained from the previous convolution.

Pooling comes in various types, depending on the method employed. In Max Pooling, the highest element from the feature map is selected. Average Pooling calculates the average of the elements within a specific image segment. Sum Pooling, on the other hand, computes the total sum of the elements in the predefined segment.

Fully connected layer: This layer's neurons are all coupled to one another. In CNN, this layer decreases the amount of human oversight. This layer flattened the image before feeding it to the thick layer. This layer is also where classification takes place.

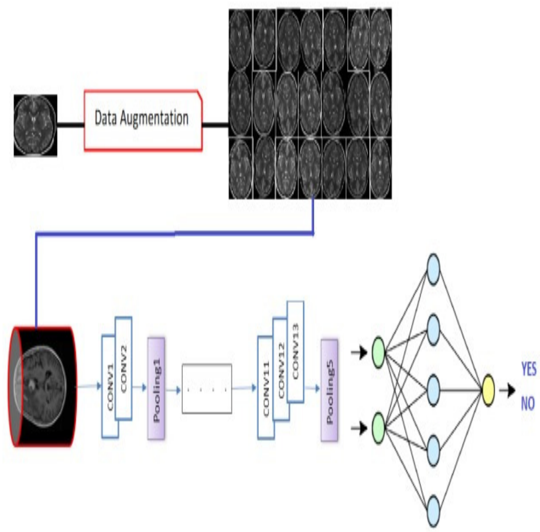

Fig 3: Working of CNN in this research

The CNN approach analyzes the entire image, in contrast to the conventional approach that employs a block-based algorithm. The current system is primarily composed of five modules: Pre-processing, Dataset Division, CNN Model Creation, Deep Neural Network Training, and Epochs. The CNN investigative model's job was to gather important information from images.

Fig 4 depicts the framework of the existing approach. The images used are sourced from various datasets, including Kaggle and BRATS datasets.

Within the dataset, multiple MRI images can be included, with one selected as the input image. During pre-processing, the image's label is encoded, and the image is resized. Data splitting entails designating 80% of all the information provided as training and 20% as validation. Subsequently, a CNN model is constructed, and deep neural network training is carried out over multiple epochs. Detection results in a binary output: "yes" if a tumour is present and "no" if there is no tumour.

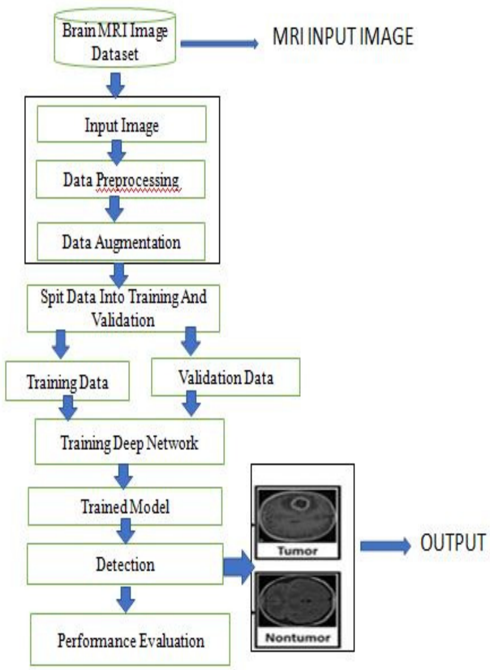

Fig 4: The structure of the existing algorithm

The initial and critical step in enhancing the quality of brain MRI images is pre-processing. Initial processing entails removing random noise and resizing images. The brain MRI image is initially converted into a greyscale image. The adaptive bilateral filtering technique is employed to eliminate unwanted noise and distortions present in the brain image. This process contributes to an improvement in both diagnostic accuracy and classification rates. During the acquisition phase, image processing begins with extracting an image from a dataset. Since further processing requires an image, this is the first step in the workflow sequence. The image that was first captured is raw. In this context, the image is processed using the local device's file path.

In the classification step, the fully connected layer links all the features to the dense layer, which is responsible for categorizing the data into two classes: "yes" or "no."

It's worth noting that this approach is designed specifically for brain tumour detection and does not involve the localization of the brain tumour within an image.

3. PRELIMINARIES:

A. Object Detection:

Combining picture categorization and object localization results in object detection. Images that are entered are categorized into two or more classes in image classification. Use bounding boxes to find the things in the image during object detection. The only purpose of the CNN algorithm is picture classification. It is unable to identify the image's objects. As a result, various object-detecting algorithms have been created.

Single-shot detectors and two-stage detectors are the two main categories of object detection algorithms. This classification is based on the amount of network iterations an input image has undergone.

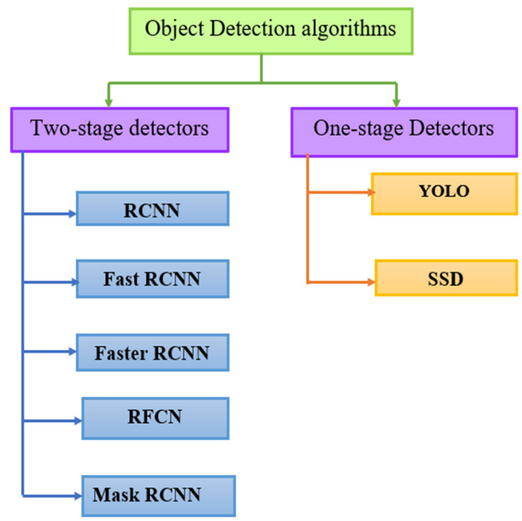

Fig 5: Classification of object detection algorithms

This object detection method carries out the following three tasks:

- In image analysis, one of the tasks is to identify regions within an image that may potentially contain objects. These areas are often referred to as "region proposals" or "region suggestions."
- Take CNN characteristics that are suggested for the region.
- Sort the objects based on the features that were extracted.

Extraction of region recommendations from the image employs a variety of techniques. They are the sliding window approach, region proposal network, and selective search. It uses the Faster RCNN algorithm in this two-stage detector.

B. The description of Faster RCNN:

A Region-Convolution Neural Network is a faster object detection architecture from the R-CNN family. The Faster R-CNN network's major goal is to establish a robust network that can perform both object detection and object localization within images. Convolution neural networks (CNNs) and Region Proposal Networks (RPNs) are combined into a single network to increase the model's speed and accuracy.

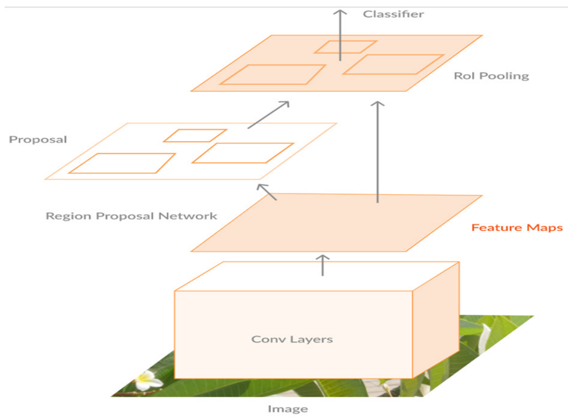

Fig 6: Faster R-CNN architecture

Fig 6 illustrates the structure of the R-CNN model, which consists primarily of two components:

1. RPN (Region Proposal Network)

2. Fast R-CNN detector

1. Region Proposal Network (RPN):

Regional proposals are produced by the RCNN and Fast RCNN models using a conventional selective search strategy. Computations require additional time. RPN, a convolutional-based network, is added to the Faster RCNN model to lower this, bringing down the proposal time for each image from two seconds to ten milliseconds.

In photos that could include objects, RPN is in charge of creating potential regions of interest (region suggestions).

The RPN makes use of the feature maps it has gotten from the CNN backbone. The RPN uses a sliding window method with anchor boxes of various sizes and shapes to indicate potential item placements on these feature maps. Throughout training, the network adjusts these anchor boxes to better match the sizes and placements of real objects. The RPN projects two parameters for each anchor.

- Modifications to the anchor's coordinate to match the geometry of the real item;
- The likelihood that the anchor contains an object (the "objectless Score").

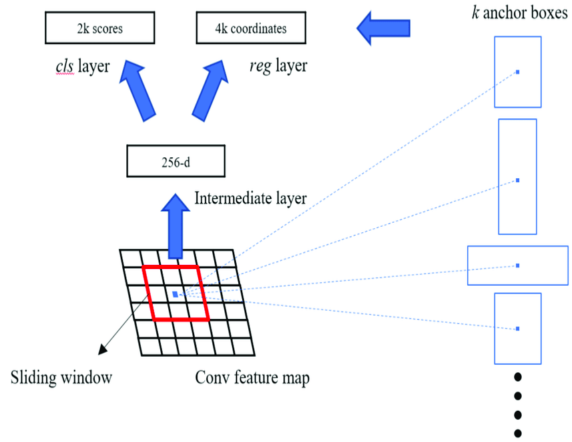

Fig 7: operation of RPN

Many of the region proposals that are produced when many are needed may overlap and point to the same thing. Here, the anchor boxes are ranked according to their objectness probability using the Non-Maximum Suppression (NMS), and the top-N anchor boxes with the highest scores are chosen. NMS makes sure that the final, chosen proposals are correct and unique. As potential region proposals, these chosen anchor boxes are taken into consideration.

2. Fast R-CNN detector:

The Fast R-CNN detector is critical in the Faster R-CNN architecture because it is responsible for recognizing items within the area of suggestions created by the Regional Proposals Networks.

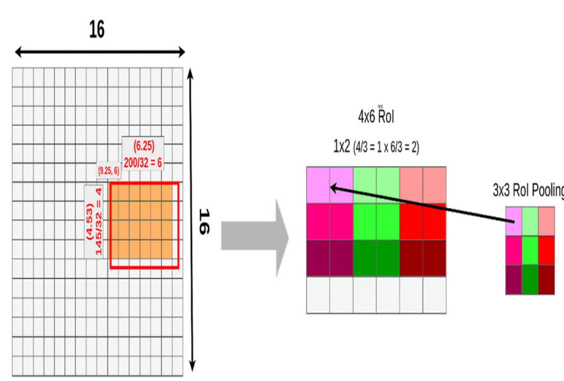

Fig 8: mechanism of RoI Pooling

Applying RoI pooling to the region suggestions made by the RPN is the first stage. Each region proposal is divided into a grid of cells with equal sizes using RoI pooling, which then applies maximum pooling within each cell. To extract useful features that capture object-specific data, the RoI-pooled feature maps are put into the CNN backbone. After that, the RoI-pooled and feature-extracted regions move through several completely connected layers. The tasks of object categorization and bounding box regression are carried out by these layers. The network's predictions of class probabilities and bounding box changes are followed by a post-processing step that improves the detection results. Non-maximum suppression (NMS) is employed in this stage to eliminate redundant detections while keeping the most certain and non-overlapping detections.

4. IMPLEMENTATION:

This approach is intended for identifying and pinpointing the location of tumours in the brain using MRI images, and it employs a faster model of R-CNN for this purpose.

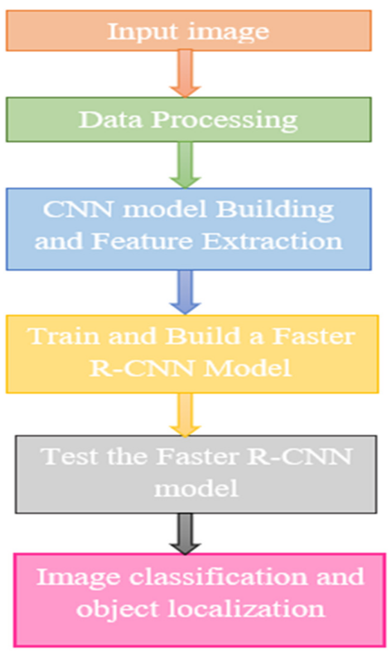

Fig 9: The structure of the implementation model

A. Input data:

The collection of data, which includes 4,600 Photos, was collected from the Kaggle tool website. Intended for both training and validation purposes. 80% of these photos are designated for training, while the other 20% are intended for validation.

B. Data processing:

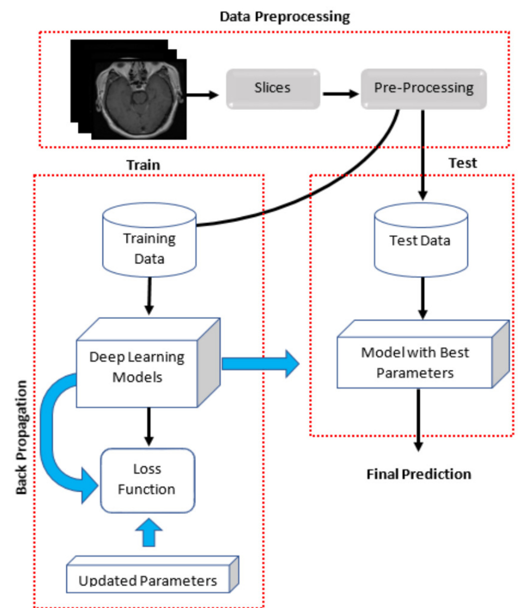

Fig 10: process of data processing

The initial and critical step in improving the quality of brain MRI images is the process of pre-processing. Essential pre-processing steps include the removal of sporadic noise and image scaling. In the initial phase, the brain MRI image is converted into a greyscale image. The adaptive bilateral filtering technique is employed to eliminate unwanted noise and correct distortions that may exist in the brain image. This pre-processing step leads to improvements in both diagnostic accuracy and classification rates.

C. CNN modelling and feature extraction:

In this study, four pre-trained CNN architectures were utilized for the classification of brain tumours. These architectures include Xception, Inception v3, Efficient Net, and Mobile Net. Keras software is a freely available Python neural network library that provides access to these models. To address the issue of overfitting, data augmentation techniques were applied, which proved beneficial in mitigating the problem associated with the limited number of images available in the dataset.

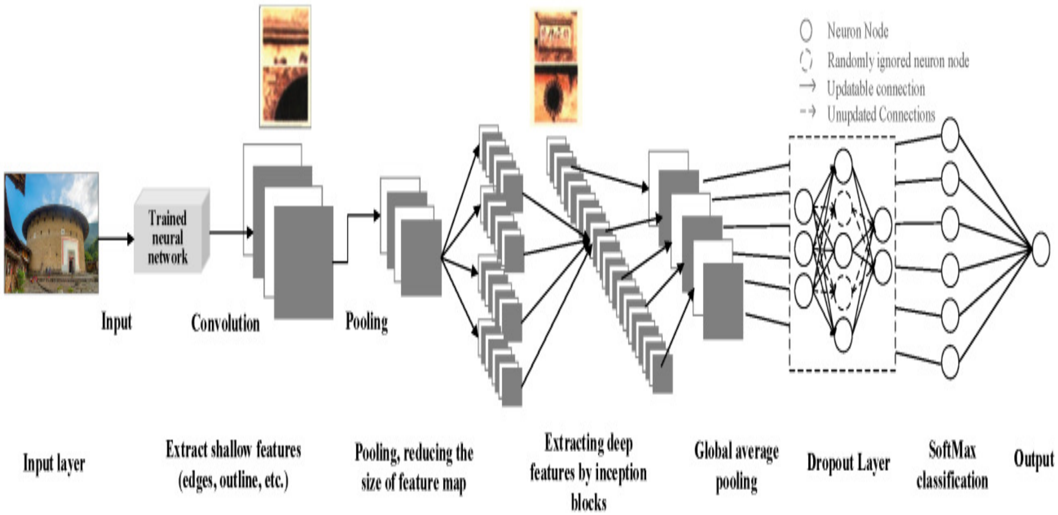

Fig 11: Process of CNN

The MRI images are given to the CNN model for future vector generation. It contains 2 convolution layers with a 3x3 kernel size and a max pooling layer with a 3x3. Then it passes through a dense layer to reduce the features by a 2. Finally, the fully connected layer connects all neurons and passes through the softmax classifier for the classification of whether it is a tumour or no tumour.

D. Training and Testing of faster RCNN model:

Initially, construct the Faster R-CNN model and proceed to train it using existing datasets. Typically, a portion of the dataset, ranging from 60% to 80% of the images, is allocated for training the model. The model's performance is assessed using the remaining 20% of the images. Regardless of the CNN's classification output (whether it identifies an image as depicting a brain tumour or not), the image is input into the system. The primary objective is to expedite the localization of tumour components through the Faster R-CNN model, which is capable of identifying and delineating tumour regions more efficiently.

5. RESULTS:

An HP Pavilion quad-core CPU and 8 GB of RAM were used for the system. Python 3 is used to write the codes. Installing libraries like Tensor Flow, Keras, Pillow, SciPy, and OpenCV-python required the Anaconda package management. The experiments were conducted using 2.5GB/12GB of Google compute engine backend (GPU) RAM on the Google Collaborator server. Using Python 3.0, TensorFlow uses Keras as its backend.

A. Evaluation Metrics:

The assessment of the model's performance involves considering several key parameters, which are calculated as follows:

- Accuracy: is computed as: Accuracy = (T_N + T_P) / (T_P + F_P + T_N + F_N) * 100.
- Precision is determined as: Precision = T_P / (T_P + F_P) * 100.
- Recall is calculated using: Recall = T_P / (T_P + F_N) * 100.
- F1-score is derived from the following formula: F1-score = 2 * (Precision * Recall) / (Precision + Recall).

In these equations, T_P represents the percentage of altered photographs that are correctly identified as such, while F_P denotes the percentage of unaltered images that are erroneously identified as altered. F_N, on the other hand, represents the quantity of altered photographs mistakenly identified as original images. T_N corresponds to the number of genuinely identified original photographs. These metrics collectively evaluate the model's performance.

Table 1: Comparison of metrics

Models	Precision %	Recall%	F1-score%	Sensitivity%	Specificity%	Accuracy%
Efficient Net-B0	97.1	97.1	97.1	97.1	97.1	97.1
Xception	96.3	96.5	96.5	96.5	96.3	96.3
Mobile net	98.5	98.5	98.5	98.5	98.5	98.5
Proposed Inception V3	99.1	99.1	99.1	99.1	99.1	99.1

B. The Results over Models:

In this method, four models are used. The performance of this method over different models is given below. Table 2 shows that the proposed approach outperforms accuracy, precision, F1 score and recall.

1. Inception v3 Model:

This model achieves an accuracy of 99.1% at no of epochs 18. The results showed out in terms of accuracy and loss curves as shown in figs 12 and 13. This model gives better accuracy for this model compared to others but coverage gives 99.1%.

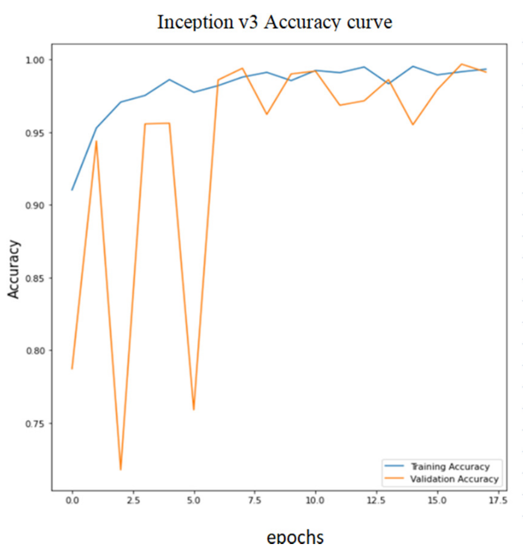

Fig 12: Accuracy values for the inception v3 model

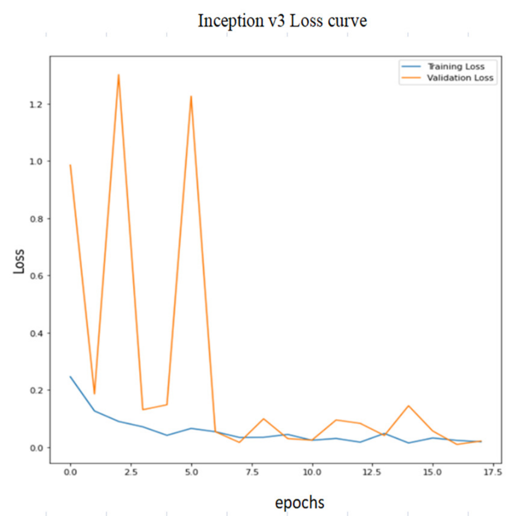

Fig 13: Loss values for the inception v3 model

2. Mobile net Model:

It attains 98.5% accuracy at no of epochs 5. The results showed out in terms of accuracy and loss curves as shown in figs 14 and 15.

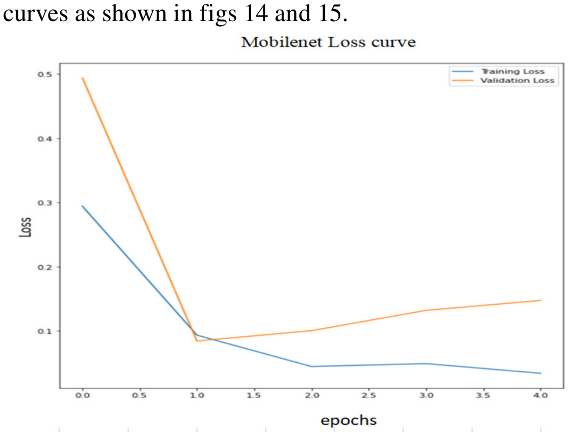

Fig 14: Accuracy values for Mobile net model

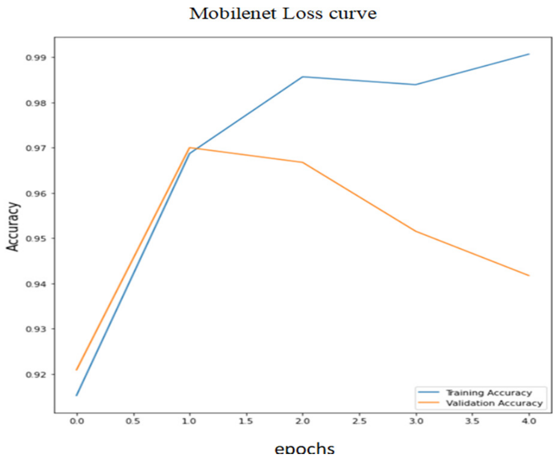

Fig 15: Loss values for the Mobile net model

3. Xception Model:

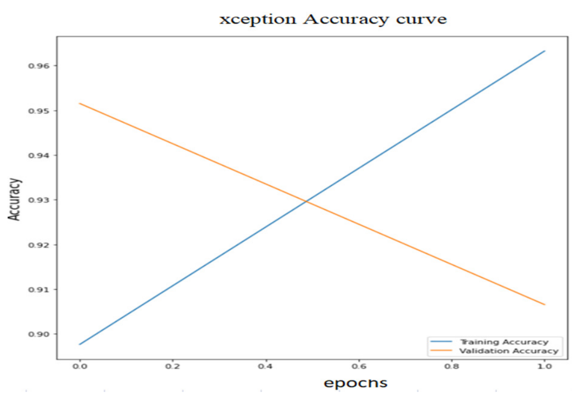

Fig 16: Accuracy values for the xception model

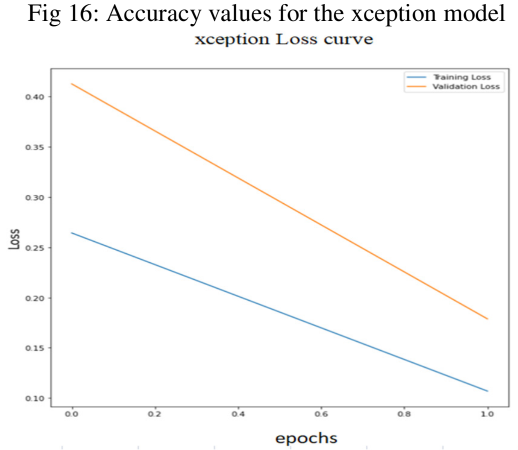

Fig 17: Loss values for the xception model

This model achieves an accuracy of 96.3% at no of epochs 20. The results showed out in terms of accuracy and loss curves as shown in figs 16 and 17.

4. Efficient net model:

This model achieves an accuracy of 97.1% at no of epochs 20. The results showed out in terms of accuracy and loss curves as shown in figs 18 and 19.

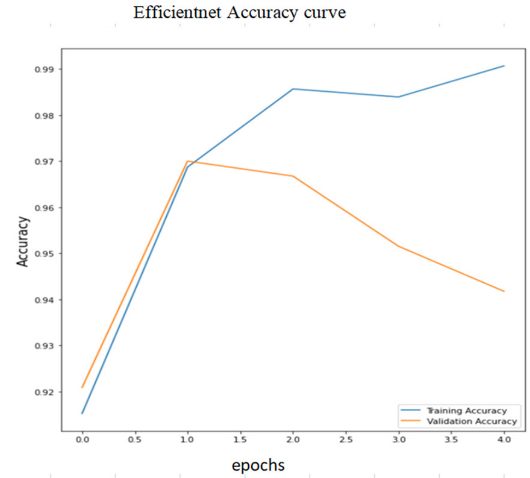

Fig 18: Accuracy values for efficient net model

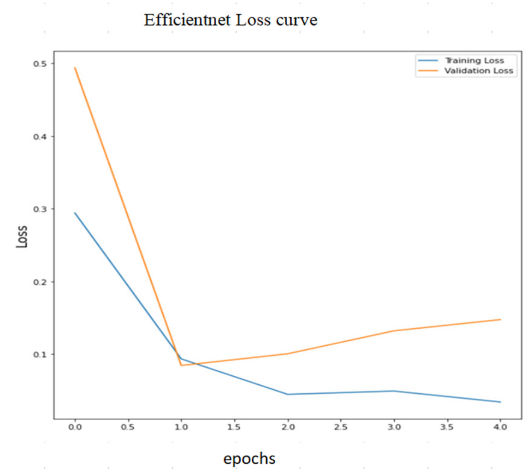

Fig 19: Loss values for efficient net model

5. Proposed result:

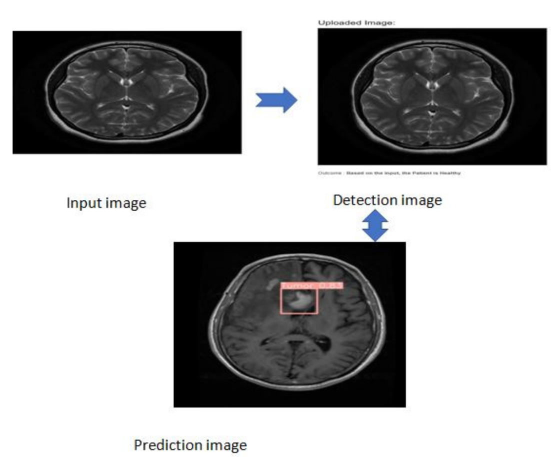

Fig 20: Implementation Result

6. CONCLUSION:

In summary, this research introduced a system for the detection of brain tumours using deep neural learning methods. The suggested methodology can identify tumour images and divide an MRI image into two categories: tumour and no tumour. The tumour portion is then located in the MRI image. The suggested approach may convert the features of a picture into feature vectors. The suggested method finds feature dependencies and correspondences automatically by utilizing the entire connection layer. To be prepared to test and then categorize the MRI pictures, the suggested model must first be trained. Additionally, it locates tumour components utilizing the object identification algorithm known as Faster RCNN. Four different approaches were used to assess the effectiveness of the suggested model: Inceptionv3, Mobile net, xception, and efficient net. The suggested method achieved 99.1% accuracy at no epochs 20 with COVERAGE models.

REFERENCES

[1] H. A. Shah, F. Saeed, S. Yun, J. -H. Park, A. Paul and J. -M. Kang, "A Robust Approach for Brain Tumour Detection in Magnetic Resonance Images Using Fine-tuned Efficient Net," in IEEE Access, vol. 10, pp. 65426-65438, 2022, doi: 10.1109/ACCESS.2022.3184113.

[2] Haitham Alsaif, Ramzi Guesmi, Badr M Alshammari, Tarek Hamrouni, Tawfik Guesmi, Ahmed Alzamil, and Lamia Belguesmi. A novel data augmentation-based brain tumour detection using a convolutional neural network. Appl Sci 12(8):3773, 2022.

[3] Hamza Rafiq Almadhoun and Samy S. Abu-Naser. Detection of brain tumour using deep learning. Int J Acad Eng Res 2022; 6(3).

[4] Fig share dataset. URL: https://figshare.com/articles/braintumordataset/1512427.

[5] Gunasekara S.R., Kaldera H.N., Kaldera M.B. A systematic approach for MRI brain tumour localization and segmentation using deep learning and active contouring. J Healthcare Eng. 2021.

[6] Masood M., Nazir T., Nawaz M., Mehmood A., Rashid J., Kwon H.Y., Mahmood T., Hussain H. A novel deep learning method for recognition and classification of brain tumours from MRI images. Diagnostics. 2021; 11(5):744.

[7] Gore, D.V.; Deshpande, V. Comparative study of various techniques using deep Learning for brain tumour detection. In Proceedings of the 2020 IEEE International Conference for Emerging Technology (INCET), Belgaum, India, 5–7 June 2020; pp. 1–4.

[8] Qureshi, S.A.; Raza, S.E.A.; Hussain, L.; Malibari, A.A.; Nour, M.K.; Rehman, A.U.; Al-Wesabi, F.N.; Hilal, A.M. Intelligent Ultra-Light Deep Learning Model for Multi-Class Brain Tumour Detection. Appl. Sci. 2022, 12, 3715.

[9] Zahoor, M.M.; Qureshi, S.A.; Bibi, S.; Khan, S.H.; Khan, A.; Ghafoor, U.; Bhutta, M.R. A New Deep Hybrid Boosted and Ensemble Learning-Based Brain Tumour Analysis Using MRI. Sensors 2022, 22, 2726. Arabahmadi, M.; Farahbakhsh, R.; Rezazadeh, J. Deep Learning for Smart Healthcare—A Survey on Brain Tumour Detection from Medical Imaging. Sensors 2022, 22, 1960.

[10] Borole, V.Y.; Nimbhore, S.S.; Kawthekar, D.S.S. Image processing techniques for brain tumour detection: A review. Int. J. Emerg. Trends Technol. Comput. Sci. (IJETTCS) 2015, 4, 2. Ranjbarzadeh, R.; Bagherian Kasgari, A.; Jafarzadeh Ghoushchi, S.; Anari, S.; Naseri, M.; Bendechache, M. Brain tumour segmentation based on deep learning and an attention mechanism using MRI multi-modalities brain images. Sci. Rep. 2021, 11, 10930.

[11] Tiwari, P.; Pant, B.; Elarabawy, M.M.; Abd-Elnaby, M.; Mohd, N.; Dhiman, G.; Sharma, S. CNN Based Multiclass Brain Tumour Detection Using Medical Imaging. Comput. Intell. Neurosci. 2022, 2022, 1830010. Anaya-Isaza, A.; Mera-Jiménez, L. Data Augmentation and Transfer Learning for Brain Tumour Detection in Magnetic Resonance Imaging. IEEE Access 2022, 10, 23217–23233. [Google Scholar] [CrossRef]

[12] Lotlikar, V.S.; Satpute, N.; Gupta, A. Brain Tumour Detection Using Machine Learning and Deep Learning: A Review. Curr. Med. Imaging 2022, 18, 604–622.

[13] Xie, Y.; Zaccagna, F.; Rundo, L.; Testa, C.; Agati, R.; Lodi, R.; Manners, D.N.; Tonon, C. Convolutional neural network techniques for brain tumour classification (from 2015 to 2022): Review, challenges, and future perspectives. Diagnostics 2022, 12, 1850

[14] Almadhoun, H.R.; Abu-Naser, S.S. Detection of Brain Tumour Using Deep Learning. Int. J. Acad. Eng. Res. (IJAER) 2022, 6, 29–47.

[15] Soomro, T.A.; Zheng, L.; Afifi, A.J.; Ali, A.; Soomro, S.; Yin, M.; Gao, J. Image Segmentation for MR Brain Tumour Detection Using Machine Learning: A Review. IEEE Rev. Biomed. Eng. 2022, 16, 70–90Cancer-Types. Brain Tumour: Statistics. 2022. Available online: https://www.cancer.net/cancer-types/brain-tumor/statistics (accessed on 15 November 2022).

[16] Usman, K.; Rajpoot, K. Brain tumour classification from multi-modality MRI using wavelets and machine learning. Pattern Anal. Appl. 2017, 20, 871–881.

[17] Musallam, A.S.; Sherif, A.S.; Hussein, M.K. A New Convolutional Neural Network Architecture for Automatic Detection of Brain Tumours in Magnetic Resonance Imaging Images. IEEE Access 2022, 10, 2775–2782

[18] Amin, J.; Sharif, M.; Haldorai, A.; Yasmin, M.; Nayak, R.S. Brain tumour detection and classification using machine learning: A comprehensive survey. Complex Intell. Syst. 2022, 8, 3161–3183.

[19] Nayak, D.R.; Padhy, N.; Mallick, P.K.; Zymbler, M.; Kumar, S. Brain Tumour Classification Using Dense Efficient-Net. Axioms 2022, 11, 34.

[20] Obeidavi, M.R.; Maghooli, K. Tumour Detection in Brain MRI using Residual Convolutional Neural Networks. In Proceedings of the 2022 IEEE International Conference on Machine Vision and Image Processing (MVIP), Ahvaz, Iran, 23–24 February 2022; pp. 1–5.

[21] Sajid, S.; Hussain, S.; Sarwar, A. Brain tumour detection and segmentation in MR images using deep learning. Arab. J. Sci. Eng. 2019, 44, 9249–9261

[22] Aamir, M.; Rahman, Z.; Dayo, Z.A.; Abro, W.A.; Uddin, M.I.; Khan, I.; Imran, A.S.; Ali, Z.; Ishfaq, M.; Guan, Y.; et al. A deep learning approach for brain tumour classification using MRI images. Comput. Electr. Eng. 2022, 101, 108105.

[23] Brain Tumour Kaggle. Available online: https://www.kaggle.com/code/sayedgomaa/brain-tumor/notebook (accessed on 21 December 2022).

[24] Mahmud, M.I.; Mamun, M.; Abdelgawad, A. A Deep Analysis of Brain Tumour Detection from MR Images Using Deep Learning Networks. Algorithms 2023, 16, 176.

[25] Bairagi VK, Gumaste PP, Rajput SH, Chethan K S. Automatic brain tumour detection using CNN transfer learning approach. Med Biol Eng Comput. 2023 Jul; 61(7):1821-1836. Doi: 10.1007/s11517-023-02820-3. Epub 2023 Mar 23. PMID: 36949356.

[26] Mahmud, Md Ishtyaq, Muntasir Mamun, and Ahmed Abdelgawad. 2023. "A Deep Analysis of Brain Tumour Detection from MR Images Using Deep Learning Networks" Algorithms 16, no. 4: 176.

[27] R. Ezhilarasi and P. Varalakshmi, "Tumour Detection in the Brain using Faster R-CNN," 2018 2nd International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC) I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), 2018 2nd International Conference on, Palladam, India, 2018, pp. 388-392, doi: 10.1109/I-SMAC.2018.8653705.

[28] A. Sinha, A. R P, M. Suresh, N. Mohan R, A. D and A. G. Singerji, "Brain Tumour Detection Using Deep Learning," 2021 Seventh International Conference on Bio Signals, Images, and Instrumentation (ICBSII), Chennai, India, 2021, pp. 1-5,

[29] Noreen, S. Palaniappan, A. Qayyum, I. Ahmad, M. Imran and M. Shoaib, "A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumour," in IEEE Access, vol. 8, pp. 55135-55144, 2020, doi: 10.1109/ACCESS.2020.2978629.

[30] A. Hossain et al., "A YOLOv3 Deep Neural Network Model to Detect Brain Tumour in Portable Electromagnetic Imaging System," in IEEE Access, vol. 9, pp. 82647-82660, 2021, doi: 10.1109/ACCESS.2021.3086624.

[31] S. Kumar, R. Dhir and N. Chaurasia, "Brain Tumour Detection Analysis Using CNN: A Review," 2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS), Coimbatore, India, 2021, pp. 1061-1067, doi: 10.1109/ICAIS50930.2021.9395920.

[32] T. Hossain, F. S. Shishir, M. Ashraf, M. A. Al Nasim and F. Muhammad Shah, "Brain Tumour Detection Using Convolutional Neural Network," 2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT), Dhaka, Bangladesh, 2019, pp. 1-6, doi: 10.1109/ICASERT.2019.8934561..