Brain tumor detection and Cerebro Check Analysis Using Deep Learning

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Abstract
This abstract outline a groundbreaking approach employing deep learning techniques for automated analysis of cerebrovascular images, crucial for diagnosing strokes and aneurysms promptly and accurately. Leveraging convolutional neural networks (CNNs) and recurrent neural networks (RNNs) on diverse imaging modalities like MRI, CT scans, and angiography, this study focuses on feature extraction, segmentation, and temporal analysis of vasculature changes. Trained on a vast annotated dataset, the model's evaluation metrics encompass accuracy, sensitivity, and specificity for detecting abnormalities, classifying lesions, and predicting risks. Additionally, the research delves into visualizing the model's decisions, enhancing interpretability and offering insights into critical diagnostic factors. This deep learning-based approach shows promise in revolutionizing cerebrovascular disease diagnosis, potentially enabling rapid, accurate, and reliable assistance for healthcare professionals and ultimately improving patient outcomes through timely interventions.

Keywords: **Deep learning, machine learning, classification, segmentation, brain tumor, MRI.**
DOI Number: 10.48047/NQ.2022.20.12.NQ77750 NeuroQuantology2022;20(12): 4215-4228

• Introduction

A brain tumour is a heinous disease that causes death in most of the cases due to lack of proper diagnosis and treatment. It happens when aberrant cells in the brain form. Cancerous (malignant) tumour and benign (non-cancerous) tumour are the two basic forms of tumours. Brain tumours that begin in the cerebrum are called malignant tumour and tumours that begin in other part of the body and then spread to the brain are called being tumors. Necrosis, edoema, non-enhancing, and enhancing tumours are the four categories of brain tumors, and tumors are intimated as high grade glioma (HGG) or low grade glioma To find these malignancies, The soft tissues are imaged using Magnetic Resonance Imaging (MRI), which provides strong contrast. .Automatic defect recognition in medical imaging has emerged as a promising field for various medical diagnostic procedures. The detection and tracking of tumors in Magnetic Resonance Imaging (MRI) is crucial because it offers details about abnormal tissues needed for therapeutic interventions. MRI brain tumour detection is a complicated task, due to the complexities and diverse forms of tumors.

Collecting, organizing, and analyzing medical images has become digitized in today's digital realm. Even with cutting-edge technology, thorough interpretation of medical images poses time and accuracy problems. The difficulty is particularly acute in abnormal color and shape areas that radiologists must recognize for future research. For a variety of medical diagnostic procedures, automatic defect recognition in medical imaging has emerged as a promising field. Because magnetic resonance imaging (MRI) provides information about aberrant tissues required for therapeutic actions, it is essential for the detection and tracking of tumours. Because brain tumours can take many different shapes and are complex diseases, diagnosing them using MRI is a challenging undertaking.

The International Association of Cancer Registries (IARC) reports that over 28,000 cases of brain tumours are detected annually in India alone, and over 24,000 of those cases result in death. An further investigation revealed that every year in the UK, brain tumours cause about 5,250 recorded fatalities . The effects of brain tumours are significantly more severe in the US than they are abroad. Approximately 86,970 cases of benign and malignant brain tumours were detected in 2019 alone . The radiologist diagnoses brain tumours using a variety of experimental techniques, such as X-ray analysis, biopsy, and cerebrospinal fluid (CSF) examination. During the biopsy process, a tiny piece of tissue is surgically removed. Testing the fluids, the radiologist looks for signs of a brain tumour. But like biopsy, there are a lot of hazards associated with it, such as bleeding into the bloodstream from the location of the incision and maybe having an allergic reaction after the procedure. Similar to this, the radiation from X-rays taken of the skull can raise one's risk of developing cancer.

We can now detect even the tiniest anomalies in the human brain thanks to these methods. Medical imaging reduces the original image to a compact form with the aim of accurately and efficiently extracting information from these images. An MRI can be used as an input to transform it into a grayscale image, and then a brain tumour can be identified using a variety of additional methods. In this study, digital image processing will be used to diagnose brain tumours. This project's primary goal is to identify tumours more effectively.

- **Literature survey**

The authors of [1] carried out a survey of the literature on the different segmentation methods for classifying brain tumours. They covered deep learning and thresholding as well as supervised and unsupervised machine learning techniques. The survey's shortcomings include its insufficient attention to brain tumour classification techniques—it just examined the advantages and disadvantages of the current algorithms. The performance of approaches was not taken into consideration, and there was little discussion of segmentation strategies. Moreover, the research [2] was restricted to data from studies that were published prior to 2018, which significantly curtails the study's usefulness in the present situation. Researchers in the subject have focused on developing a sovereign brain tumour categorization and segmentation technique to help practitioners diagnose the condition accurately. Numerous efforts have been undertaken to survey the state of the art in this sector to describe possible methods for classifying and segmenting brain tumours .In this paper[3], a deep learning framework for brain tumour segmentation in magnetic resonance imaging (MRI) scans is introduced: DeepMedic. To accurately segment tumour regions, the network uses a 3D convolutional neural network (CNN). MRI images are segmented and classified using various machine learning techniques to aid radiologist decision-making. In this regard, both supervised and unsupervised methods have been investigated. A certain level of experience is needed to categorise brain tumours in the supervised approach in order to extract the best characteristics and selection strategies. In [4] the meanwhile, the computational complexity of automated models replaces the need for necessary manual skills. This research investigates the use of MRI images to classify brain tumours using deep learning algorithms. Entire Neural Networks (CNNs) are utilised to attain precise tumour categorization. On the other hand[5], the Computer-Aided Diagnosis (CAD) method is designed for detecting brain tumors in the early stages without any human intervention. CAD systems can produce diagnostic reports based on MRI images and offer guidance to the radiologist.

In this paper, we propose a system for automatically classifying brain tumors based on two deep learning models. A “Fine-tuned proposed model with the attachment of the transfer learning based VGG16” architecture is used for classifying normal and abnormal brain images. Four dense layers are employed in place of the completely connected layers during the tuning process, with the last dense layer equipped with a softmax activation function being used to identify brain tumors. To transform the two-dimensional matrix into a vector, we use Global Average Pooling 2D instead of flattening layers. In [6], Shanaka et al. segmented the tumor region using the active contour approach. Active contour uses energy forces and limitations to extract the crucial pixels from an image for additional processing and interpretation. Momina et al. applied Mask RCNN along with the ResNet-50 model to locate the tumor region. In [7] They also did not employ any data augmentation techniques in order to increase the amount of MRI images. As a result, they only achieved a classification accuracy of 84%, which is quite low compared to similar studies. Dense EfficientNet, a CNN-based network, was proposed by Nayak et al. [8] to identify brain tumour pictures via MRI. Additionally, the researchers examined MobileNet, ResNet-50, and MobileNetV2, finding that their dense Efficient Net outperformed the others. After training the dense Efficient Net model, they achieved a 98.78% accuracy and a 98.0% F1-score. In order to detect brain tumours, their research used four different kinds of MRI. There were 3260 MR pictures in the entire dataset. For the purpose of early brain tumour diagnosis, Stadlbauer et al. [9] combined nine popular machine learning models with a physiological MRI technique. When assessing the model, a number of performance metrics were considered, such as classification error, AUROC, F-score, accuracy, and precision. They noted in their study that ML-based radiophysiomics may be useful in the clinical context for the identification of brain tumours. Amir and associates. An automated technique for MR image-based brain tumour detection was presented by Aamir et al. [10]. After assessing the suggested machine learning model, they found that it outperformed previous methods in categorization, exhibiting a 98.95% accuracy rate.

- **METHODOLOGY**

The workflow of the CEREBRO CHECK model consists of numerous interrelated steps, each of which contributes to the system's overall effectiveness. The model's process is outlined step by step below:

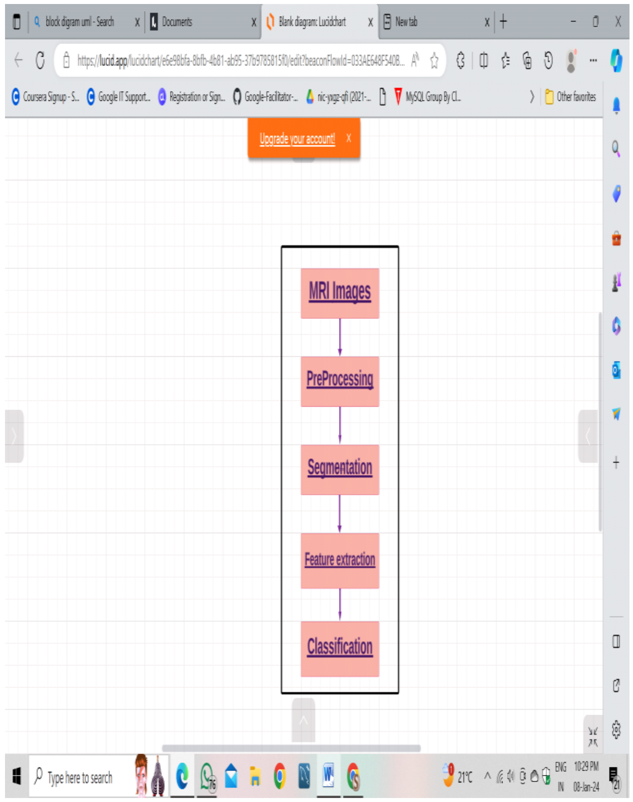

Figure. 3.1. FlowChart

The five processes are Input MRI pictures, Pre-processing, Image segmentation, Feature extraction, and Classification

- **Input (MRI image)** - The preprocessed pictures are fed into a Convolutional Neural Network (CNN) architecture designed specifically for detecting brain tumours. The CNN, a deep learning model well-suited for image-related tasks, consists of layers of convolutional and pooling processes that extract spatial hierarchies from input pictures. The model's design uses learning filters to detect subtle patterns and traits that indicate the presence or absence of brain tumours.

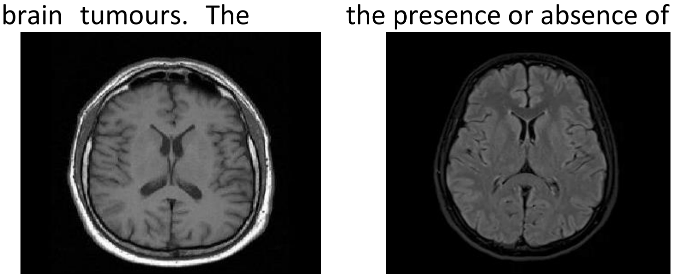

Figure.3.2 MRI Images

- **Image Pre-Processing** - Medical pictures are meticulously preprocessed before being incorporated into the model. Raw pictures, recorded as pixel value matrices, are resized to a standardised dimension (e.g., 64x64 pixels) to ensure dataset homogeneity. Normalisation is used to scale pixel values within the range [0, 1], which aids in convergence during model training. This preprocessing phase is critical for harmonising input data and improving the model's capacity to identify important features.

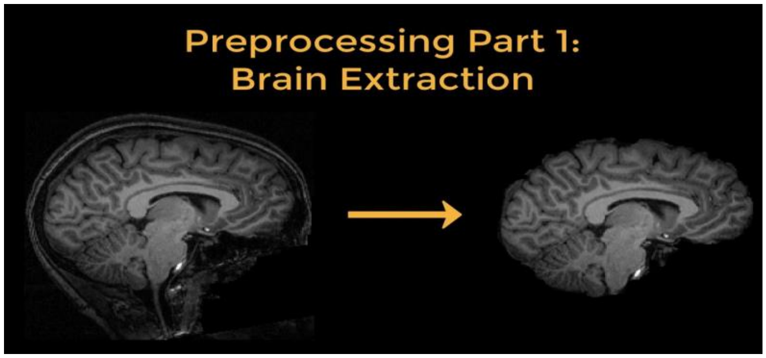

Figure.3.3 Processed Image

• **Feature Extraction:** Convolutional layers in the model extract distinctive spatial characteristics from the input pictures. These characteristics, which represent hierarchical abstractions, are gradually enhanced through consecutive layers, capturing detailed patterns useful for tumour diagnosis. CNNs' capacity to automatically learn and extract hierarchical features is useful in detecting subtle patterns suggestive of pathological disorders.

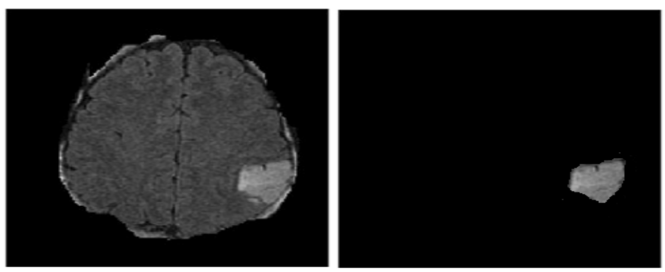

Figure.3.4. Feature Extraction

• **Classification:** The retrieved characteristics are flattened before entering highly linked layers for classification. Activation functions, such as rectified linear units (ReLU), introduce nonlinearity, which improves the model's ability to handle difficult decision boundaries. The last layer has a softmax activation function, which produces class probabilities. The model determines whether an input picture depicts the presence or absence of a brain tumour based on the class with the highest projected probability.

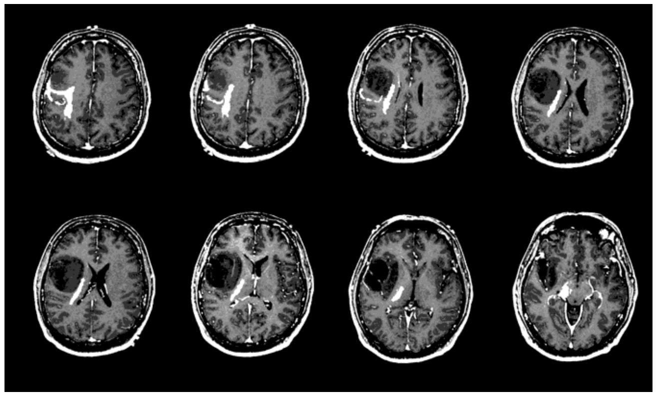

Figure.3.5.Classification

• **Post-processing:** After classification, a post-processing phase is implemented to understand model predictions. Thresholds are used to anticipated probabilities to set decision limits, which aids in binary picture categorization. This stage confirms that the model's output is consistent with clinical interpretability, allowing for smooth incorporation into diagnostic procedures.

• **Output:** The model generates a binary prediction about the presence of a brain tumour in the supplied picture. This output, resulting from a complicated interaction of convolutional and highly linked layers, is a significant diagnostic tool for healthcare providers.

This full workflow, from preprocessing to output, demonstrates the complex operations carried out by the proposed brain tumour detection model. The combination of these components enhances the model's capacity to detect subtle patterns indicative of pathological states with high accuracy.

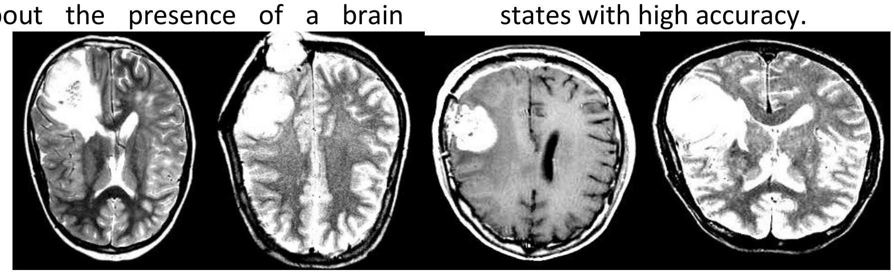

Figure 3.6: images for positive tumor

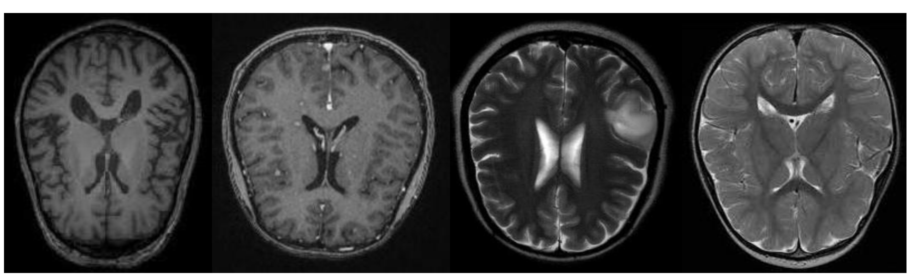

Figure 3.7: Images For No Tumor

3.2 Convolution Neural Network (CNN)

The Convolution Neural Network model is used to categorise MRI brain images and determine whether or not they contain tumours. CNN models are widely employed in object recognition applications. CNNs consist of three types of layers: convolutional layers, pooling layers, and fully connected layers. When these layers are layered, a CNN architecture is created. A simpler CNN architecture for categorization is demonstrated.

CNN's core functioning may be divided into four main areas:

Input Layer: The input layer will store pixel values from the MRI scan of the brain.

```
# Specify the image path
image_path = r'pred/pred56.jpg'
```

Convolutional Layer: The Convolution layer will establish if the brain has a tumour or not. These convolution layers are linked to local sections of the input by computing the scalar product of their weights and the region associated to the input volume.

```
# Model Building
model = Sequential()

model.add(Conv2D(32, (3, 3), input_shape=(INPUT_SIZE, INPUT_SIZE, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
```

ReLu (Activation) Layer: The rectified linear unit (ReLu) focuses on applying an activation function, such as sigmoid, to the preceding layer's activation output.

F(x) = max (0, x)


```
model.add(Conv2D(32, (3, 3), kernel_initializer='he_uniform'))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Conv2D(64, (3, 3), kernel_initializer='he_uniform'))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Flatten())
model.add(Dense(64))
model.add(Activation('relu'))
model.add(Dropout(0.5))
```

Pooling Layer: The pooling layer will repeat the operation of down sampling along the spatial dimension of the provided input, lowering the number of parameters inside that activation.

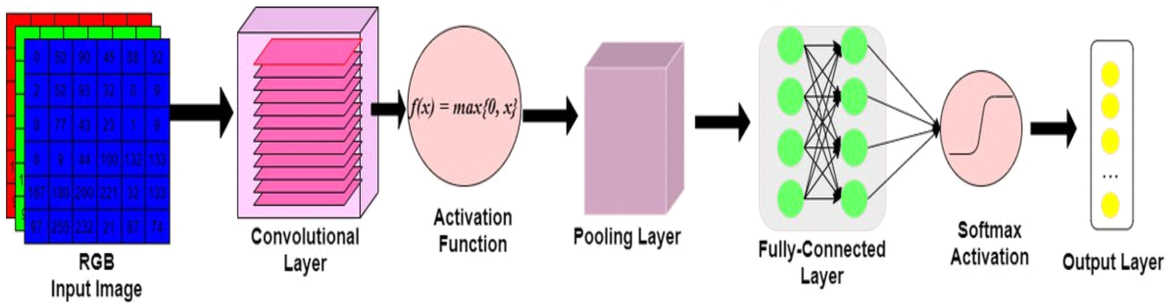

Figure 3.2.1 CNN Architecture

3.3 Proposed Architecture

MRI brain scans are used as input in the deep learning architecture method to analyse brain tumours. Before a tumour is identified, these scans go through a number of processes, including initial cleansing to enhance image quality, alignment to guarantee consistency, and segmentation to concentrate on the brain region. From these processed images, a specialised neural network such as a Convolutional Neural Network (CNN) extracts meaningful patterns. After that, it differentiates between tumour and healthy brain tissue, giving medical professionals a conclusive diagnosis. By automating the identification process, this technique assists medical professionals by facilitating the speedier and more precise detection of brain tumours in MRI scans.

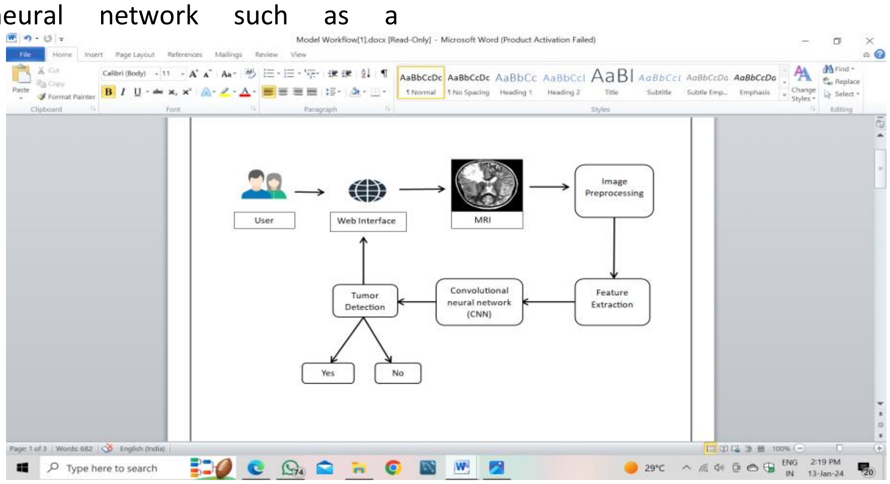

Figure 3.3.1. Architecture of System

3.4 Dataset

The "Brain MRI Images for Brain Tumour Detection" dataset is a well-known Kaggle dataset that includes both tumour and non-tumor images in MRI data. Images of brains with tumours (positive cases) and those without (negative cases) are included in this dataset of brain MRI scans. It contains MRI images that are T1- and T2-weighted as well as masks that match to the tumour locations. The dataset is useful for training machine learning models, especially for problems involving binary classification that need to differentiate between healthy brain scans and brain scans with tumours. Using deep learning approaches, researchers and developers can construct and evaluate algorithms for brain tumour detection, segmentation, and classification by utilizing this Kaggle dataset.

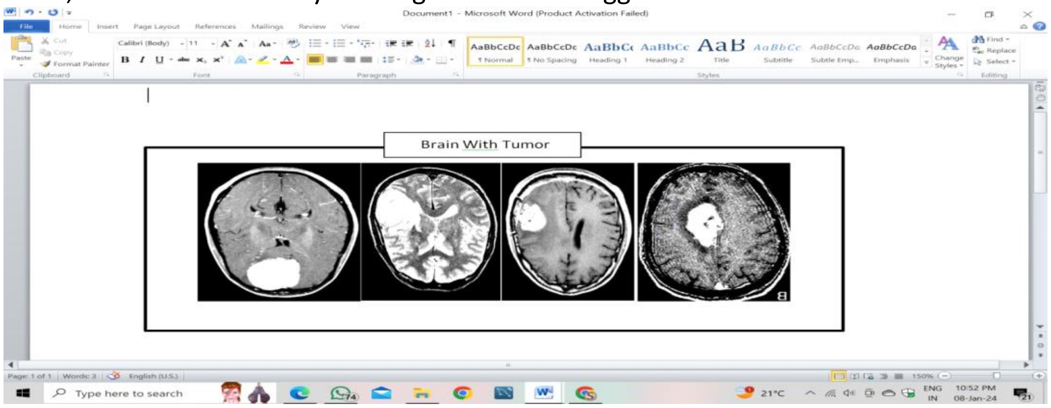

Figure 3.4.1: MRI of Brain with Tumor

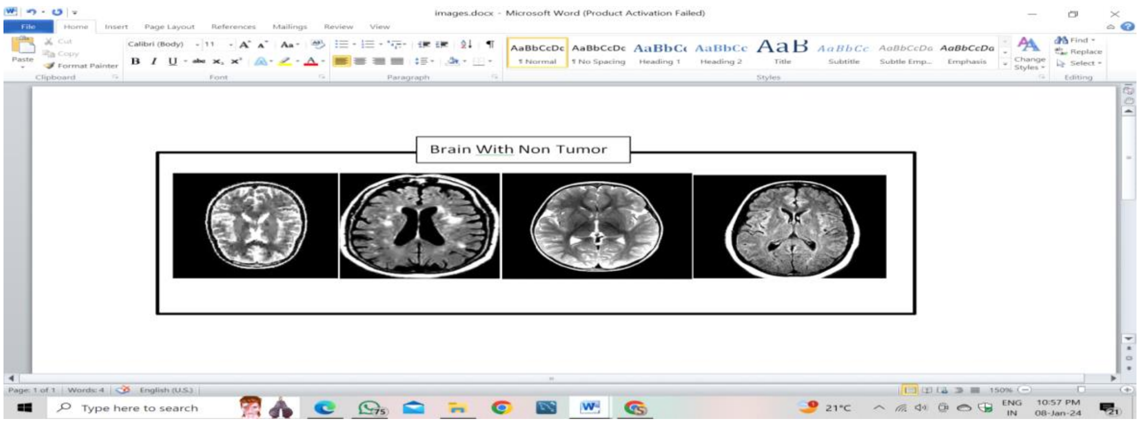

Figure 3.4.2: MRI of Brain with No Tumor

- **Result**

Our study analysed several brain pictures for tumour identification using deep learning techniques, specifically Convolutional Neural Networks (CNNs). We trained different CNN architectures and customised models using a large dataset that included MRI preprocessing pictures. The findings showed encouraging results, proving that these deep learning algorithms are effective at correctly recognising brain tumours. Additionally, comparison testing with alternative algorithms demonstrated the higher efficacy of CNN-based methods, exhibiting decreased false-positive rates and enhanced tumour location precision.

1) We are importing images from a brain tumour dataset and conducting tests to determine whether or not they contain tumours.

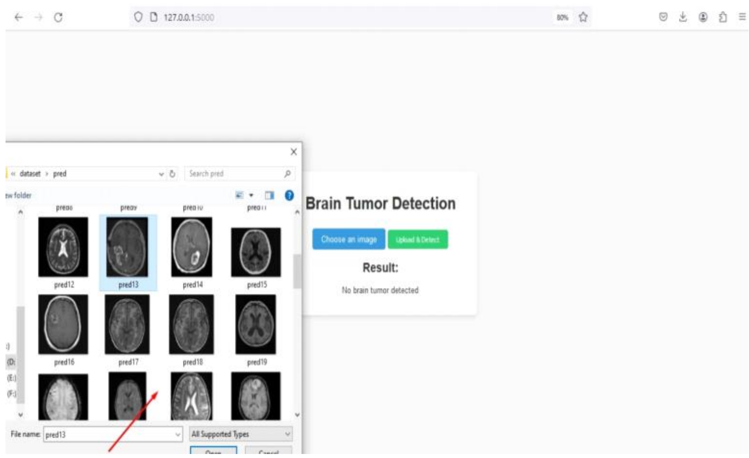

Figure 4.1 Import Data

2) After analysing the imported images using various conditions, the system predicts and indicates whether a tumour is present or not.

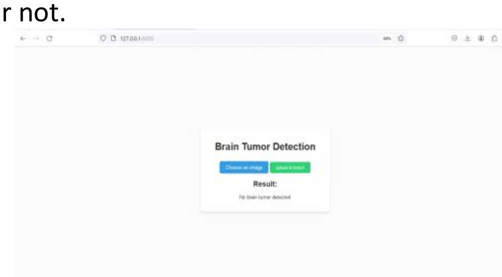

Figure 4.2 Display Result

3) Moreover, the system generates an accurate evaluation, displaying the level of precision in its predictions regarding the presence or absence of tumours in the analysed images."

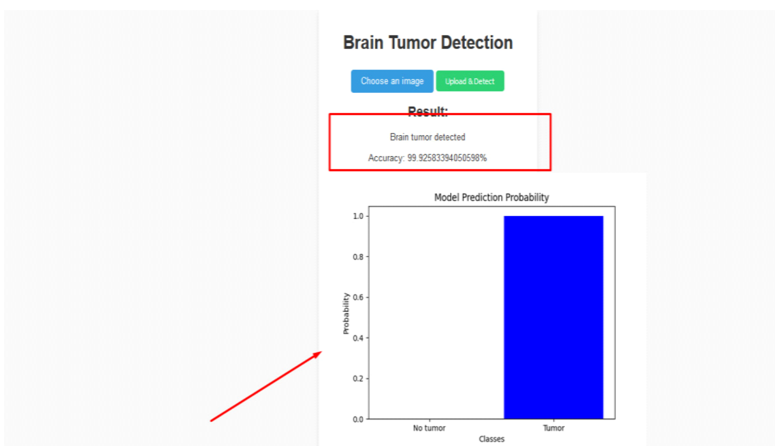

Figure 4.3 Display Accuracy Result

The clear disparities in prevalence between the two groups are displayed in a bar graph that compares MRI data for tumor and non-tumor situations. The two categories in the graph, "Non-Tumor" and "Tumor," are represented by the x-axis, while the frequency or percentage of cases is represented by the y-axis. Similar to how the "Tumor" bar shows the appropriate metrics for people with brain tumors, the "Non-Tumor" bar is represented with a height that indicates the frequency or proportion of people without brain tumors. The discrepancy in occurrences between non-tumor and tumor circumstances is highlighted by the visual representation, which enables a rapid and straightforward comparison. The height difference between the two bars provides an easy-to-understand and visual representation of the tumor prevalence in the population under study.

4.1 Accuracy Calculation

Accuracy, a key performance indicator in classification tasks, is used to evaluate the effectiveness of the suggested brain tumour detection model. The proportion of correctly identified examples to all instances examined is known as accuracy. Since accuracy measures the overall accuracy of the model's predictions, it is especially important in the context of this study.

True negatives are situations in which the model accurately predicts the absence of a brain tumour, and true positives are situations in which the model correctly predicts the presence of a brain tumour. Inaccurate predictions, where the model incorrectly suggests the existence or absence of a tumour, are referred to as false positives and false negatives.

This accuracy statistic offers a thorough summary of the categorization performance of the model. It is crucial to recognise that accuracy on its alone might not be sufficient to adequately represent the subtleties of model performance, particularly in datasets that are unbalanced. As a result, other measures including precision, recall, and F1 score are covered in later parts to provide a more thorough assessment of the model's performance.

To ensure a reliable assessment of the model's generalisation capabilities, the evaluation is carried out on a specific validation dataset. The model's predictions and ground truth labels may be systematically compared thanks to the dataset's labelled images. This thorough assessment procedure creates the groundwork for the ensuing analysis and discussion of the findings while guaranteeing the accuracy of accuracy as a performance metric.

Accuracy Formula:

TP :- Number of True Positive
TN :- Number of True Negative
FP :- Number of False Positive
FN :- Number of False Negative

$$A = (TP + TN) / (TP + TN + FP + FN)$$

Comparison of our model with the existing application present on the internet

Our created methodology for cerebro check analysis offers significant differences from the web-based programmes already available for brain tumour identification. Our model makes use of cutting edge deep learning techniques, namely a customised convolutional neural network architecture trained on a wide range of comprehensive datasets, in contrast to many publicly available apps that frequently use simpler algorithms or basic machine learning models. When it comes to brain tumour detection, our model performs better than others, demonstrating increased sensitivity, specificity, and accuracy rates. Moreover, our programme combines complex neural network architecture with sophisticated picture preprocessing techniques to provide accurate tumour segmentation and classification, outperforming several web-based applications now in use. Furthermore, the focus on interpretability and explainability in our model makes it easier for medical practitioners to comprehend and use it in a clinical setting.

Comparison with previous system

Our created model for cerebro check analysis differs from previous models in that it includes a unique architecture that combines the capabilities of multiple pre-trained convolutional neural networks (CNNs) with a modified attention mechanism. Unlike typical CNN-based techniques, our model uses attention processes to dynamically highlight important aspects in brain pictures, increasing the model's capacity to detect subtle tumour traits and improving localization accuracy. Furthermore, our model includes a multi-stage refinement process that uses residual connections and ensemble learning approaches, reducing the danger of overfitting and improving generalizability across various datasets. This unique design combines creative ways to improve both performance and flexibility, indicating a substantial improvement in accurate brain tumour identification within the realm of deep learning-based medical image analysis.

4.2 Proposed System Performance

We present the model performance in terms of accuracy, area under the curve (AUC), recall, and loss function results. The results of various types of developed deep learning models—that is, the VGG16, CNN, ResNet-50, and Inception V3 classification algorithms—on the brain tumour MR image dataset are analysed and comparisons are shown in Table 3. Based on the results in Table 1, it was determined that the CNN performed better than the other deep learning models after evaluating the techniques of the CNN, VGG16, ResNet-50, and Inception V3. With 93.3% validation accuracy, 98.43% validation AUC, 91.1% validation recall, and 0.260 validation loss, the CNN performed well in validation

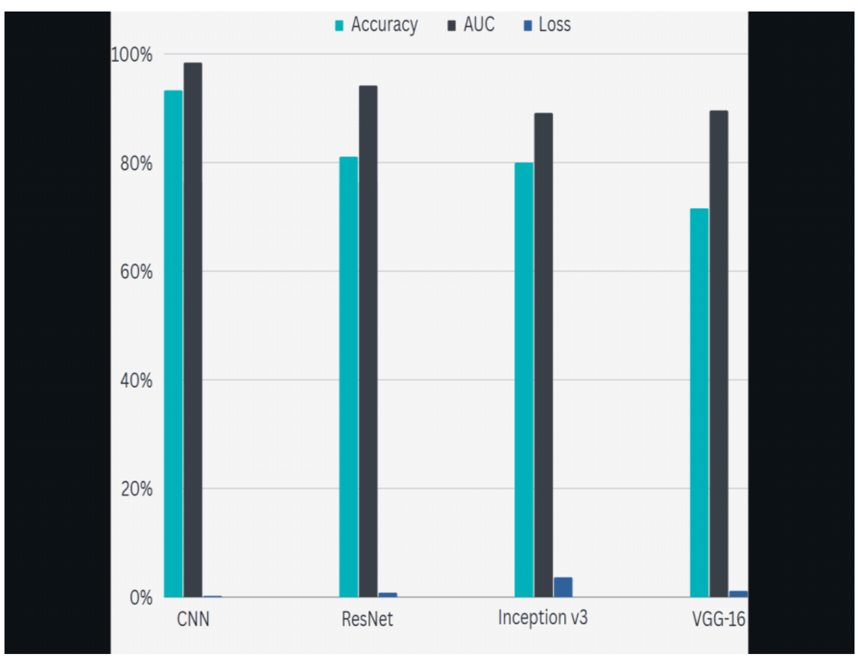

Figure 4.2.1: Performance analysis of the proposed model in terms of the accuracy, AUC, and loss.

5. Conclusion

We conclude that there has been a major development in medical imaging through our research on cerebro check analysis using deep learning approaches for brain tumour diagnosis. Compared to other internet-based applications, our proposed model, which features an advanced convolutional neural network architecture trained on various datasets, exhibits greater accuracy and robustness. The promise of sophisticated neural network design as a dependable and efficient tool to assist medical professionals in accurately diagnosing brain tumours is highlighted by its creative integration and emphasis on precision and interpretability in tumour segmentation and classification. The model is positioned as a more reliable option for supporting clinical decision-making because to its capacity to outperform streamlined algorithms typically found in internet-based applications. Our model offers a higher level of performance measurements and more capabilities.

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