Intracranial-Tumor Detection and Classification System using Convnet and Transfer Learning

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Abstract - *Intracranial tumors simply known as brain tumors have proven to be one of the pressing causes of human mortality globally. One of the most challenging responsibilities in medical image processing nowadays is the detection of brain malignancies. These tumor types are formed by a mass of aberrant cells, and the percentage of individuals diagnosed with brain cancer is growing in relation to the aging population, which is a global health concern. Early identification and diagnosis of brain disorders can have a significant impact on efforts to treat them. Given the aforementioned, deep learning approaches can assist notably in overcoming the above-stated challenges. In detecting and classifying brain/intracranial tumors from Medical Resonance (MR) images, which is one of the advanced methods in the field of medicine, we developed a deep learning model and deployed it to a web application that works using Convolutional Neural Networks (ConvNet) based on Transfer Learning (TL). This system is capable of identifying and distinguishing tumors among three major classes of brain tumors which are; Glioma, Meningioma, Pituitary, and normal images as well with very high accuracy.*

Key Words: Intracranial tumor, Brain tumor, ConvNet, Transfer Learning, MRI, Deep Learning, Detection.

1. INTRODUCTION

One of the most prevalent cancers in the world is brain tumours. These tumours occur in the brain and spinal cord and are usually caused by uncontrolled cell manipulation. The symptoms of brain tumours vary based on the part of the brain affected. These include headaches, weakness, vomiting, seizures, blurred vision, fever and more. Most patients experience progressive weakness and altered mental function as the tumour grows. Many dies from secondary complications caused by the tumour-related illness. Even though treatments are available, doctors need to detect brain tumours early to save patients' lives.

Doctors use a number of techniques to detect brain tumours. CT scan is one of them that uses X-rays to create 3D image of the patients' inner organs and structures. Magnetic Resonance Imaging (MRI) is an advanced version of CT scan that uses stronger magnetic fields and transverses greater length and breadth. MRIs are also effective at detecting soft tissue anomalies like tumours and cysts. In addition, doctors use advanced biochemistry techniques to determine if there are any diseases like cancer in the patients' body. Blood tests can also reveal if there are cancerous growths or diseases in the bloodstream that affect the brain's blood vessels.

An aberrant mass of cells growing within or outside of your brain is called a brain tumour. Brain tumours can be malignant, which is cancerous, or non-cancerous which is known as benign.

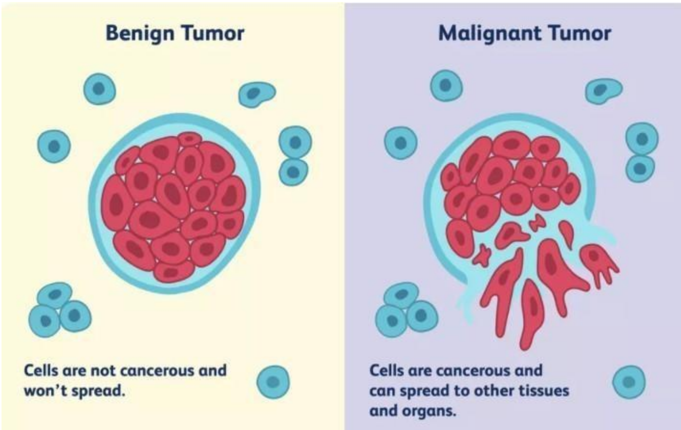
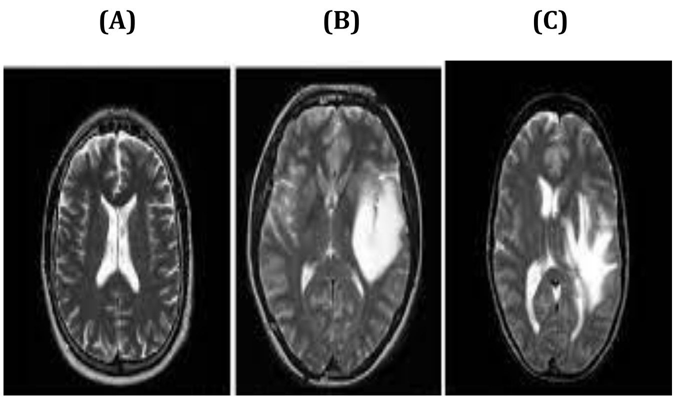


Fig.1. Illustrations of Cancerous & Non-Cancerous Cells



(a)Normal image. (b)Non-Cancerous (Benign). (c)Cancerous (Malignant).

Fig.2. Illustrations of Normal, Benign, and Malignant images.

While some tumours enlarge swiftly, others do so slowly [1]. Around one-third of brain tumours are cancerous (malignant), Nevertheless, whether or not they are malignant, brain tumours can affect your health and the way your brain functions if they enlarge to the point where they strain on nearby tissue, blood vessels, and nerves. Primary tumours are tumours that form in the brain. Secondary tumours are cancers that develop in another area of the body before spreading to the brain. There are at least 120

different kinds of brain tumours and Central Nervous System (CNS) disorders. In 2021, brain and CNS cancers will be the cause of 18,600 adult deaths and 3,460 deaths in children under the age of 15 according to the American Cancer Society [2]. The National Brain Tumour Society (NBTS) has identified some of the frequent symptoms of brain tumours, these are highlighted below;

Fatigue or muscle weakness	Seizures
Difficulty thinking, speaking or finding words	Changes in personality or behaviour
Difficulty with balance or dizziness	Weaknesses, numbness or loss of movement in one part
Memory Loss	Headaches
Unexplained nausea or vomiting	Confusion in everyday matters or disorientation

Fig.3. Symptoms of brain tumours

[14]. Magnetic Resonance (MR) images are analysed for abnormalities and choices are made by a physician or radiologist as part of the conventional procedure for finding brain cancers. However, it heavily depends on a doctor's medical knowledge; differences in levels of experience and the characteristics of pictures make a diagnosis with the naked eye more difficult [3]. Considering that they have a number of irregularities or noisy data, the images are difficult for a doctor to assess in a short amount of time. Interpreting a large quantity of data becomes increasingly difficult as the volume of information rises. A brain tumour's manual identification becomes increasingly time and money-consuming. Deep learning, specifically neural networks, accelerates considerable significance when it achieves positive outcomes. Convolutional Neural Networks (CNNs) excel in gaining abilities and offering infinite accuracy. Many applications for deep learning have been proposed, such as voice recognition, object detection, pattern classification, as well as other decision-making tasks [4], [5].

Impact of Deep Learning and Artificial Intelligence in Medical Imaging: Convolutional Neural Networks (CNN) in medical imaging is primarily responsible for igniting interest in deep learning. Convolutional Neural Networks CNN is a potent method for learning meaningful representations of pictures and some other structured data. Deep learning has the potential to advance healthcare, and there is room to deploy models that can cut administrative costs while enhancing patient needs. [6]. Over time, deep-learning medical imaging technology has been utilized in numerous sectors. These include chatbots that are driven by AI and can recognise trends in patients' symptoms. Deep learning algorithms have been vital in the identification of certain malignancies, pathology, diagnosis of unusual disorders, and identification of various tumours. Deep learning is essential to each of these fields because it gives the medical expert insights that enable early problem detection and highly customised and pertinent patient treatment. The method that specifies the task and the data is hidden behind the intricacy of the artificial intelligence, neural network, and computer that runs deep learning. These deep learning algorithms have been utilised to improve the outcomes in a variety of medical imaging fields, such as the study of brain tumours, breast cancer, and abnormalities of the head and neck.

2. EXISTING SYSTEM

When it comes to identifying and studying brain tumours, magnetic resonance imaging is the best option. The MRI will produce a large amount of data and specifics about the tumour when it examines a brain tumour. A radiologist will always have a huge amount of sources to draw from when establishing a diagnosis, but few testing tools.

Numerous attempts to evaluate multiparameter quantitative MRI data to assess the information content of the organ's afflicted region have been made, but their impact has been significantly less than that of standard MRI research [22].

They typically comprise two phases: localization and characterization. Their variability and accuracy may be controlled in two ways: by automating ROI collection and standardising quantitative feature extraction, respectively.

The bulk of methods depend on one of the alternative viewpoints: segmentation approaches are conventional that focused on a few basic MRI maps, while a preliminary manual ROI delineation is devoted to more sophisticated feature extraction methods. Through the use of image processing tools, the size of the brain tumour is calculated. The technique can only be used on cancers that resemble one another; it cannot be used on newly discovered tumour kinds. We have thus concluded that we need to train the device with a range of tumour types in order to increase tumour detection accuracy.

A variety of deep learning neural networks have been employed by other frameworks, such as Artificial Neural Networks (ANN), to create accurate results, but such plans and systems required a lot of hardware computing, which led to slower yields.

3. PROPOSED SYSTEM

In this study, we proposed an automated brain tumour detection, segmentation, and classification system. When Magnetic Resonance Imaging (MRI) produces images of the inside of the brain, the system will detect if any part of the image has tumour, if the region of the tumour is found, the algorithm used in the system will help in categorizing the kind of tumour that is present in the image. And a report stating the condition of the detected image will be produced by the system.

4. LITERATURE REVIEW

Deep learning and image processing techniques have been proposed by researchers in identifying and categorising brain tumours. Some of the most recent approaches are presented in this literature.

Brain Tumour Identification and Classification of MR images using deep learning techniques by (Zheshu Jia and Deyun Chen), in this paper, based on deep learning methods, a Fully Automatic Heterogeneous Segmentation Utilising Support Vector Machine (FAHS-SVM) has been developed for the segmentation of brain tumours. The current study suggests the inclusion of a novel, totally automated approach based on anatomical, morphological, and relaxometry features to separate the entire cerebral venous system into MRI imaging [7]. A Robust Approach for Brain Tumour Detection in Magnetic Resonance Images Using Finetuned EfficientNet by (Hasnain Ali Shah, Faisal Saeed, et al.), using a deep Convolutional Neural Network (CNN), their suggested layers are optimised to effectively categorise and detect brain tumour pictures using the EfficientNet-B0 based model. Applying multiple filters is one of the image enhancement strategies used to improve the quality of the photos [8]. Optimized Edge Detection Technique for Brain Tumour Detection in MR Images by (Ahmed H. Abdel-Gawad et al.), in this paper, a method for identifying the edges of a brain tumour using an MR scan of the patient's brain is suggested. First of all, the picture properties are enhanced using the Balance Contrast Enhancement Technique (BCET), which gives medical images superior characteristics. Then, using the relevant training dataset, the suggested Genetic Algorithms (GA) edge detection method is used to identify the fine edges [9]. A New Convolutional Neural Network Architecture for Automatic Detection of Brain Tumours in Magnetic Resonance Imaging Images by (Ahmed S. Musallam, Ahmed S. Sherif et al.), The proposed design has a few convolutional, max-pooling layers and training rounds, making it a computationally light model. When evaluated on a dataset of 3394 MRI pictures, an exceptional accuracy of 98.22% is obtained, in recognising glioma, meningioma, pituitary, and normal images [10]. Brain Tumour and Glioma Grade Classification using Gaussian Convolutional Neural Network by (Muhammad Rizwan, Aysha Shabbir et al.), They proposed a method to identify different types of brain cancers utilising two datasets and a Gaussian Convolutional Neural Network (GCNN). To categorise tumours into pituitary, glioma, and meningioma, one of the datasets is employed. The other one distinguishes between Grades 1, 2, and 3 of gliomas [11]. Data Augmentation and Transfer Learning for Brain Tumour Detection in Magnetic Resonance Imaging by (Andres Anaya-Isaza and Lionel Mera-Jimenez), in this paper, they evaluate how several conventional data augmentation techniques affect the ResNet50 network's ability to identify brain tumours. And they included a principal component analysis-based technique. The network trained from zeros and transfer learning from the ImageNet dataset were used for the training. They were able to acquire an F1 detection score of 92.34% [12]. Machine Learning and Deep Learning Approaches for Brain Disease Diagnosis: Principles and Recent Advances by (Protima Khan, MD Fazlul Kader et al), The goal of this study was to discover the best effective method for identifying various brain illnesses that may be used to further treatment in the future. And they have suggested very good techniques [13]. Towards Real-Time Computing of Intraoperative Hyperspectral Imaging for Brain Cancer Detection

Using Multi-GPU Platforms by (Giordana Florimbi, Himar Fabelo, et al.), The most effective application created in this research that makes use of Graphic Processing Unit (GPU) technology is that, it can effectively fulfil the real-time limitation set at one minute for surgical operations by classifying the largest picture in the database in less than 3 seconds. [15]. Combining Noise-to-Image and Image-to-Image GANs: Brain MR Image Augmentation for Tumour Detection by (Changhee Han, Leonardo Rundo, et al.), To enhance the DA impact with the GAN configurations, they developed a two-step GAN-based DA that creates and refines brain Magnetic Resonance (MR) pictures with or without tumours independently. They carefully examine the outcomes of CNN-based tumour classification, taking into account pre-training on ImageNet and removing odd-looking GAN-generated pictures. The findings demonstrate that, in tumour identification as well as other medical imaging tasks, their two-step GAN-based DA can considerably outperform the standard DA alone [16]. Segmentation C- Means Clustering with Spatial Information for Image

Segmentation by (Malathi Hong-Long et.al), in this paper, for the categorization of Brain MRI, a desegregation wave entropy technique based mostly on spider net plots and probabilistic neural networks was presented. For classification, the proposed approach employs two steps: a wavelet entropy-based mainly spider net plot for feature removal and a probabilistic neural network for classification [17]. Transfer Learning Based Image Visualization Using CNN by (Santosh Giri and Basanta Joshi) Compute feature vectors using a feature extraction component of the Inception v3 model and retrained the classification layer using these feature vectors. With the Caltech101 dataset, the artificial neural network architecture's mean testing precision was 98%, while with the Oxford 17 Flower picture dataset, it was 92.27% [20]. A Study on CNN Transfer Learning for Image Classification by (Mahbub Hussain, Jordan J. Bird, and Diego R. Faria), In order to determine if such a CNN architectural model (i.e. Inception-v3) will perform best in terms of accuracy and efficiency with fresh image datasets using Transfer Learning, this work suggests the research and examination of it. The retrained model is assessed, and the outcomes are contrasted with several cutting-edge methods [21]. All these are works that are related to the system we are referring to in this research paper.

5. METHODOLOGY

Classifying images of brain tumours is a crucial step in medical image processing. It helps physicians develop precise diagnoses and treatment regimens. One of the primary imaging methods used to examine brain tissue is Magnetic Resonance Imaging (MR imaging). Magnetic Resonance Imaging (MRI) generates high-quality images of the intracranial, and the method we have used in this system is that, after the magnetic resonance (MR) imaging generates the images, the system will accept them and first try to check if any area in the image is cancerous, secondly, if the system detects the area, it will further classify which type of cancer is there in the image. Otherwise, it will generate a report that the image is normal. His method introduced a novel strategy for distinguishing four unique classifications: glioma, meningioma, pituitary, and normal images.

Convolutional Neural Network: A deep learning algorithm called ConvNet or CNN in short can take photos as input, identify distinct objects in the image, and then distinguish one image from another. In order to categorize the MRI-produced input images, we employed the ConvNet approach.

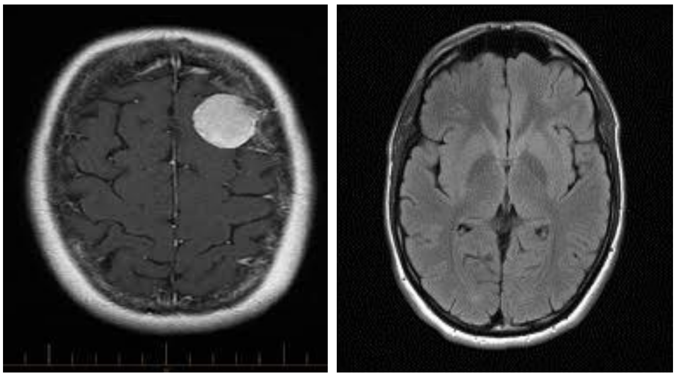
Transfer Learning: Implementing a model that has already been learned to solve a new problem is called the Transfer Learning (TL). Therefore, in this model, we used the approach of the TL and also bespoke CNN to train the model to compare accurate findings. This is highly prevalent in deep learning since it can be used to train deep neural networks that have a little quantity of data.

Prediction: Simply said, the prediction entails highlighting the aspects of the data that have the most bearing on the results of the model. Each row from the prediction array, which contains four alternative values for the corresponding labels, has been processed using the argmax function. by using the argmax function, we are able to determine the index associated with the projected outcome as seen below. The largest value that is in each row reflects the expected output out of the four potential possibilities.

Dataset: We utilized almost 1500 images of various types of brain tumours to train the model, and we also developed a test model with 500 related images. A team of four persons (Sartaj Bhuvaji, Ankita Kadam, Prajakta Bhumkar, and Sameer Dedge) created the dataset and posted it to the Kaggle website. [17]. The dataset comprises images of all three kinds of brain cancer, as well as the normal images indicated in the methodology section.

(A) (B)

(A) (B)



(a)Glioma (b)Pituitary (c)Meningioma (d)Normal

Fig.4. Sample of images from each class of brain tumours generated from the MRI.

This approach divides its work into some steps to create an effective structure for identifying cancerous and non-cancerous images; these stages are critical for achieving greater classification accuracy. The phases are described below.

i. Data collection: The initial step after logging into the system is to upload high-quality intracranial images produced by magnetic resonance imaging (MRI). Additionally, the system will store every image that is submitted and maintain a copy of it in a separate folder.

ii. Pre-Processing: The process of transforming unstructured data into a form that can be used by a deep learning or machine learning model is called data pre-processing. An essential part of the workflow is data preparation, based on the fact that the data needs to be altered so that a computer can use it. In order to prepare the data for training and testing, the pre-processing stage is helpful.

iii. Segmentation: The clipped area of the Magnetic Resonance Image is utilized as the ROI (Region of Interest) once the brain tumour has been found. Using this ROI, the Active Contour Segmentation Algorithm, sometimes known as "snakes," divides the tumour region [19]. When creating a contour algorithm, the boundary is the first step. They often take the form of spline curves and are distributed in a certain way according to the application being used. The curve is drawn, producing a picture with various sections and the growth procedures used in this process are carried out using the energy function.

iv. Feature Extraction: In this stage, we consider the pre-trained network as an independent feature extractor when executing deep learning feature extraction, letting the incoming picture to progress further, pausing at the pre-specified level, and using the outcomes of that layer as our features. So, we can still use the powerful, discriminative properties that Convolutional Neural Network (CNN) has learned. They can also be used to identify subjects that CNN was not instructed on.

v. Detection: In the detection step, it begins when intracranial MRI images are uploaded to the system, the system will attempt to identify the presence of tumours in the input image among the three different types of brain tumours—gliomas, meningiomas, and pituitary—as well as in the normal images that are tumour-free.'

vi. Classification: Giving a label from a predetermined list of categories to an input image is known as image classification. Therefore, at this stage, the system will have to identify the type of tumour present in the picture after identifying cancers from the input images. And it will also notice that there isn't a tumour if there isn't one in the image.

vii. Output Report: The input picture will reach this step after passing through all the previous stages of the system, where the outcome will be formed. If an infected image is discovered, the system will provide a report outlining the specific ailment. The system will then provide the final results and a recommendation about the tumour that was found such as the tumour's name, its signs, and the steps you need to follow to treat it.

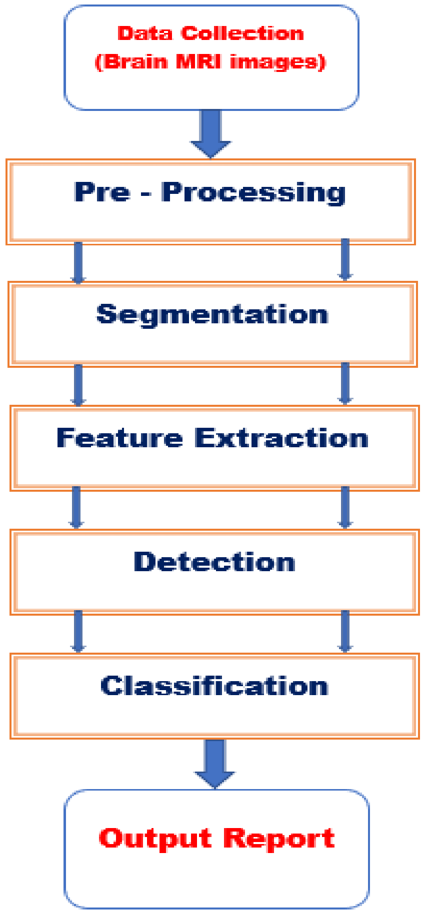


Fig.5. Architecture of the system.

Software used:

1. Computer with a core i-3 processor.
2. Framework: Flask and Streamlit.
3. Integrated Development Environment (IDE): Data scientists can create and share documents that incorporate equations, live code, and computational output using the open-source Jupyter Notebook online tool. We have picked it for the system's construction because it is utilized for many different data science activities, such as deep learning, machine learning, and many more. Secondly, we deployed the model after it was created in the Jupyter notebook with the help of a sublime text editor and visual code studio, which comprises three separate programming languages (HTML, CSS, and JavaScript).

6. RESULT

The results of this system's implementation are displayed below. Prior to performing the illness classification, the high-quality brain cancer pictures produced by Magnetic

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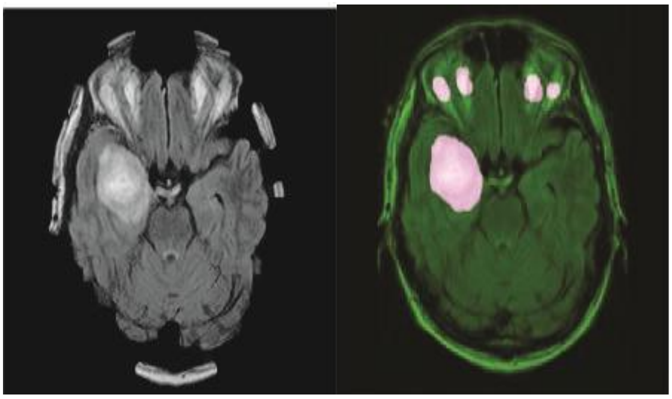
Resonance Imaging (MRI) are analysed and then features are extracted using Convolutional Neural Networks (ConvNet).



Extracted image **Detected image**

Fig.6 Demonstration of result with five detected tumours

Sensitivity and specificity are two metrics used in machine learning to assess a model's performance. Specificity is the proportion of genuine negatives that the model properly predicts, whereas sensitivity is the fraction of true positives that the model correctly predicts.

Terms;

a. TP (True Positive): Tumour exists and detected.

b. FN (False Negative): Tumour exists and not detected.

c. FP (False Positive): Tumour does not exist and is detected.

d. TN (True Negative): Tumour does not exist and has not been detected.

Sensitivity =TP / (TP+TN); which means there is successful detection of a tumour.

Specificity = TN / (TN+FP); it means there is successful detection of a healthy image.

Accuracy = TN+TP / (TN+TP+FN+FP); it means there is successful detection of a tumour.

	precision	recall	f1-score	support
0	0.97	0.93	0.95	42
1	0.91	0.91	0.91	23
2	0.93	1.00	0.96	38
3	1.00	0.97	0.98	32
accuracy			0.96	135
macro avg	0.95	0.95	0.95	135
weighted avg	0.96	0.96	0.96	135

Fig.7. The Performance of the system

Figure 7 illustrates the system's performance by evaluating the model on the support, precision, recall, and f1-score metrics. The precision, recall, and f1-score metrics all acquired scores of 0.95, or 95% when multiplied by 100. Additionally, the model's total accuracy was 96%. Fig 8 shows the actual accuracy of the system.

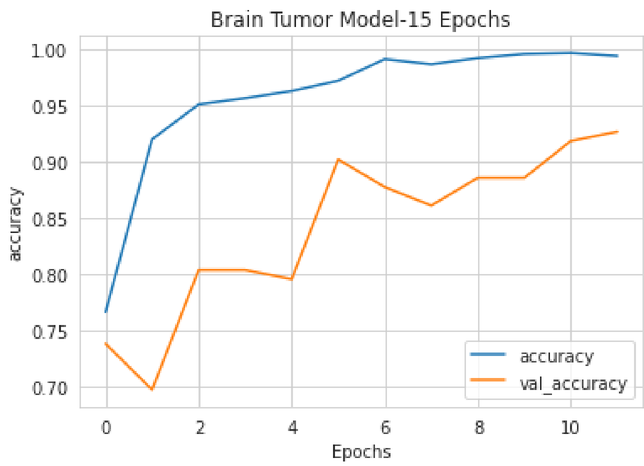


Fig.9 Training and Validation Loss Curves of the proposed model.

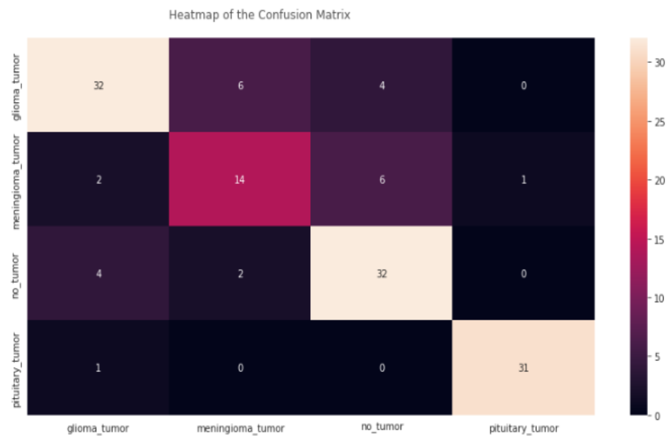


Fig. 10 Confusion matrix of the proposed model.

In the table below, we gathered information on the previous models for brain tumour detection and their respective accuracies as well. The table shows the comparison of this our system and those already existing.

References	Model and Method	Accuracies
Latif et al. [23]	SVM	96%
Khan et al. [24]	VGG-19	94%
Yahyaouni et al. [25]	DenseNet	92%
Bhathele et al. [26]	Hybrid Ensemble	95.2%
Murthly et al. [27]	CNN Ensemble	95%

Table 1. Comparison of the existing systems.

Prediction: I've used the argmax function since each row of the prediction array below contains four values for the corresponding labels. The highest number in each row is the expected result out of the four potential scenarios.

I can thus determine the index linked to the expected result using argmax.

```
[ ] pred = model.predict(X_test)
    pred = np.argmax(pred,axis=1)
    y_test_new = np.argmax(y_test,axis=1)
```

```
[ ] pred
```

```
array([0, 0, 2, 1, 0, 0, 0, 3, 2, 2, 2, 3, 1, 3, 1, 0, 2, 2, 2, 2, 0, 3,
       3, 0, 3, 3, 1, 3, 3, 0, 1, 1, 2, 2, 1, 2, 0, 1, 3, 1, 1, 0, 1, 1,
       0, 1, 0, 0, 0, 3, 2, 2, 0, 2, 0, 3, 2, 3, 0, 3, 0, 3, 0, 2, 0, 3,
       2, 0, 0, 2, 0, 2, 2, 2, 3, 2, 3, 2, 0, 1, 3, 0, 2, 2, 2, 0, 3, 0,
       1, 2, 0, 0, 3, 0, 3, 0, 3, 1, 2, 2, 1, 1, 2, 1, 0, 2, 2, 1, 3, 2,
       2, 2, 3, 0, 3, 2, 0, 3, 3, 3, 2, 1, 0, 1, 2, 3, 2, 3, 2, 0, 0, 1,
       0, 2, 0])
```

Fig. 11 Prediction Array

7. CONCLUSIONS

In this study, a system is developed that would assist doctors to diagnose brain disorders from the pictures produced by MRI while resolving concerns with human intracranial tumours. The MRI pictures are often evaluated by doctors; thus this system will now be very helpful in lowering load and labour to the doctors as they will just need to use this system to detect and classify cancers whenever they receive images from the MRI.

This system could be enhanced in the future to become a standard physical machine and will be recommended to attach it to the MRI physically to create a single machine that will perform all the tasks, including generating high-quality images, detecting diseases, and classifying different types of diseases detected all at a time.

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