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# A Model for Brain Tumor Detection Using a Modified Convolution Layer ResNet-50

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***Abstract* - Tumors are the second most prevalent type of cancer, posing a serious concern to many individuals due to their unregulated tissue development. Efficient approaches for identifying tumors, particularly brain cancer, quickly, automatically, precisely, and correctly, are crucial in the medical industry. When cancer is appropriately recognized, early identification plays a critical role in effective treatment, ensuring patient safety. Tumors form as a result of uncontrolled cell development, causing the slow degeneration of brain tissue as they consume resources meant for healthy cells and tissues. While Magnetic Resonance Imaging (MRI) is used to examine images to establish tumor location and size, the procedure is inefficient and time-consuming. The suggested model's key tool is the Convolutional Neural Network (CNN) model ResNet-50, which achieves an impressive accuracy rate of 81.6 percent. As expected, the model's performance exceeds expectations.**
***Keywords:* CNN, Brain Tumour, MRI, Deep Learning**

## I. INTRODUCTION

One of the most challenging medical illnesses to cure is a brain tumour. At this early stage in the formation of the tumour, the radiologist's ability to conduct an efficient and effective analysis is crucial (Chen, H., *et al.,*2021). A stereotactic biopsy test serves as the foundation for histological grading, which is the accepted gold standard for identifying a brain tumour's grade. In order to collect tissue for a biopsy, a portion of the skull must be cut (Badisa, H. *et al.,*2019). There are several hazards associated with the biopsy, such as bleeding from the brain and tumour, which could result in infection or even death. While the accuracy rate of stereotactic biopsy is not 100%, the main concern is that its use may result in a considerable diagnosis error and subsequent inappropriate therapeutic therapy of the condition (Rifai, H., 2021).

Since brain tumour patients find tumour biopsy to be challenging, non-invasive imaging techniques such as "Magnetic Resonance Imaging (MRI)" have become increasingly popular in the analysing of brain disease. This calls for the creation of tools that use MRI data to recognize and forecast the grade of tumours (Gu, X., *et al.,* 2021). However, accurately visualizing tumour cells and distinguishing them from surrounding soft tissues can be challenging when using imaging modalities. This could be due to a variety of factors, such as the availability of low-illuminating options within "imaging modalities," the abundance of data, or the "complexity and variance" of tumour-like unstructured shapes, viable sizes, and unpredictable tumour locations (Amin, J., *et al.,* 2021).

## II. CNN IN BRAIN TUMOUR DETECTION

Convolutional neural networks are widely used in image processing, classification, segmentation, and other auto-correlated data applications. (CNN). Comparable to swiping a filter over an input signal is a convolution. The number of parameters in a neural network is increased exponentially by layers. This can make training a model computationally demanding (and occasionally impractical). Having to change so many things at once could be a difficult task. CNNs shorten the time required to modify these parameters (El Kader, I. A.*et al.,* 2021).

CNNs are neural networks in which every node is linked to every other node. When it comes to lowering the number of parameters while maintaining model quality, convolutional neural networks (CNNs) excel. High-dimensionality images are well-suited to CNNs because of their above-mentioned capabilities (each pixel is considered a feature). In addition, CNNs were originally designed to handle pictures, but they have also made significant strides in the field of text processing. The edges of any object may be detected by CNNs since they are taught to do so.

A sliding window that is smaller than the input matrix can be used to reduce the dimensionality. Intuitively, we consider only a small fraction of the entire picture at a time. The square patch, that moves from left to right and from top to bottom, serves as the window for the entire scene? One can train a tiny regression model to recognise a certain object in a photograph, such a puppy or some grass. Assume that the image is in black and white (with no shades of grey) and that the image's patch is displayed as it is in the window (Bhandari, A. *et al.,* 2020). Images may be classified using CNNs since the notion of dimensionality reduction works well with the large number of factors (Grampurohit, S., *et al.,* 2020).

People in the United States are diagnosed with cancer at a rate of 11 percent to 12 percent per year because of the rapid development of tumours in a short period of time. As a result of all of these possibilities, we are able to create a brain tumour detection model (Hossain, T.,*et al.,* 2019).The sooner a brain tumour is diagnosed, the better the prognosis. MRI scans are noted for their high resolution. Medical expertise is required to interpret the MRI results, which reveal the tumour's exact location and size with pinpoint accuracy. MRI scans are often used in medical diagnostics because they provide more accurate findings. Because of this, MRI is becoming more popular, with a lot of room for growth (Irmak, E. 2021). Detection of cancers at an early stage is now achievable because to improvements in "computational intelligence and machine learning". The MRI scan of the brain is shown in the fig.1. (Sai, J. G. S., *et al.,* 2019-2020).

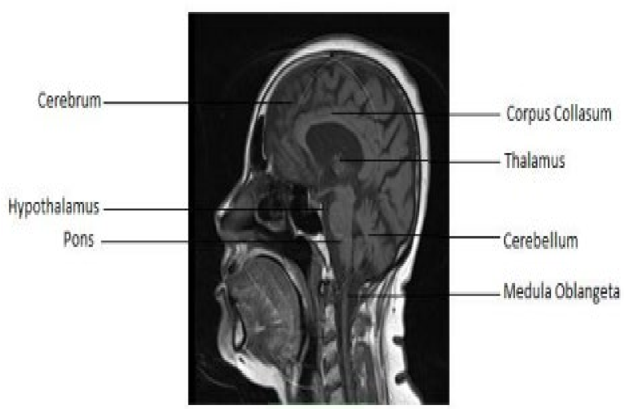


Fig. 1 Brain Image obtained from MRI Scanning

Brain tumour identification is carried out using machine learning and deep learning algorithms in several research articles. The radiologist can make decisions more quickly thanks to these projections. There are numerous ways available right now to identify tumours, and while it is unclear whether one is the best in terms of training and testing time required or accuracy. As a result, these questions emphasize a need to evaluate the literature.

## III. LITERATURE REVIEW

Applying MRI pictures, several works have been created to identify brain cancers. This section, we will go over all the methods used to diagnose brain tumors, including traditional image processing, a machine learning strategy based on CNN and neural networks and others. A real-time dataset of tumors with different sizes, shapes and intensities was used in the experimental work. For the study's conventional classifier, we constructed a Convolutional Neural Network (CNN) with keras and Tensor flow, which performed better than the traditional neural networks. Our analysis indicates that CNN has a 97.87 percent accurate rate.

Traditional classifiers and deep learning approaches follow a convolutional neural network in the authors' algorithm for segmenting brain tumours from 2D MRI images. We've used a variety of MRI pictures to train the model, including images of tumours of varied sizes, shapes, and intensities. We use "TensorFlow" and "Keras" in "Python" to build our suggested solution since it is a fast programming language (Chattopadhyay, A., & Maitra, M. 2022).

The diagnosis of brain tumours by magnetic resonance imaging (MRI) has grown in popularity, especially in the medical field. Brain tumours can only be detected or classified by MR imaging, which takes a great deal of time, effort, and knowledge from all parties involved. This highlights the importance of creating a paradigm for brain tumour self-diagnosis. Using a deep convolutional neural network (DCNN), we are able to identify brain tumours from magnetic resonance pictures. There are 253 brain MR images in the dataset used in this investigation, 155 of which are said to show cancer.

Our method has a 96 percent success rate in identifying malignancies in MR images. In the test dataset, the precision of 0.93, sensitivity of 1.00, and F1-score of 0.97 outperformed the state-of-the-art methods for brain tumour diagnosis. Additionally, the proposed model has an AUC score of 0.95, a Cohen's Kappa score of 0.91, and an average precision-recall score of 0.93. Healthcare professionals may find the proposed model helpful in confirming whether the patient has a brain tumour, hence expediting the treatment procedure (Bakr Siddiaue, M. A. *et al.,* 2020)

Convolutional Neural Networks (CNNs) have recently become essential in the medical and computer vision industries, with applications such as tumour identification in the brain. Pre-processing is used to prepare pictures for analysis by transforming them to greyscale to guarantee equal intensity. However, RGB content is present in MRI. Using median and high-pass filters, unwanted noise is removed from the photos. CNN's deeper architectural design makes use of tiny kernels. Finally, using this network to segregate tumours in MRI images produces improved results (Kumar, G., *et al.,* 2021)

Each segmented tissue is subjected to a GLCM method (gray-level-co-occurrence matrix) to identify significant properties, which are subsequently optimized using a genetic algorithm (Arif, M., *et al.,* 2022)

The survey found various accuracy rates in traditional classification approaches used in brain tumour detection a comparative chart is presented in Table I.

TABLE I COMPARISON OF THE TRADITIONAL CLASSIFICATION APPROACHES

| Model | Accuracy % |
|---|---|
| CNN | 83.7 |
| CNN-small filter | 88 |
| CRF | 62 |
| HMV | 85 |
| 3D fully connected | 84.7 |
| Integrated hierarchical | 73 |
| Local independent projection | 75 |
| RG + MKM + U-NET | 90 |
| HOG + LBP + deep features | 96.11 |
| Multi-scale 3D with fully connected CRF | 90 |
| DWAE model | 96.55 |

## IV. PROPOSED MODEL

The main objective and driving force behind this research is to develop a unique CNN architecture to grade (classify) brain tumours by using CNN's Resnet-50 model to identify the different types of tumours. The block diagram of the proposed methodology is shown in Fig.2. This section delves deeply into the following subsections.

CNNs are a typical type of neural network used in picture identification and classification. Three categories are used by CNN to divide its programming. Le Net, Alex Net, Google Net, and RESNET-50-are a few of them. CNN's main application is image categorization. The image is inputted into the computer as an array of pixels. Convolutional Neural Networks (CNNs) represent a specialized category of neural networks specifically tailored for the intricate tasks of picture identification and classification. These networks are distinguished by their unique architecture, incorporating convolutional layers, pooling layers, and fully connected layers. CNNs excel in automatically learning hierarchical features from images, enabling them to capture intricate patterns and details. Among the notable categories within the CNN framework are LeNet, AlexNet, GoogleNet, and RESNET-50.

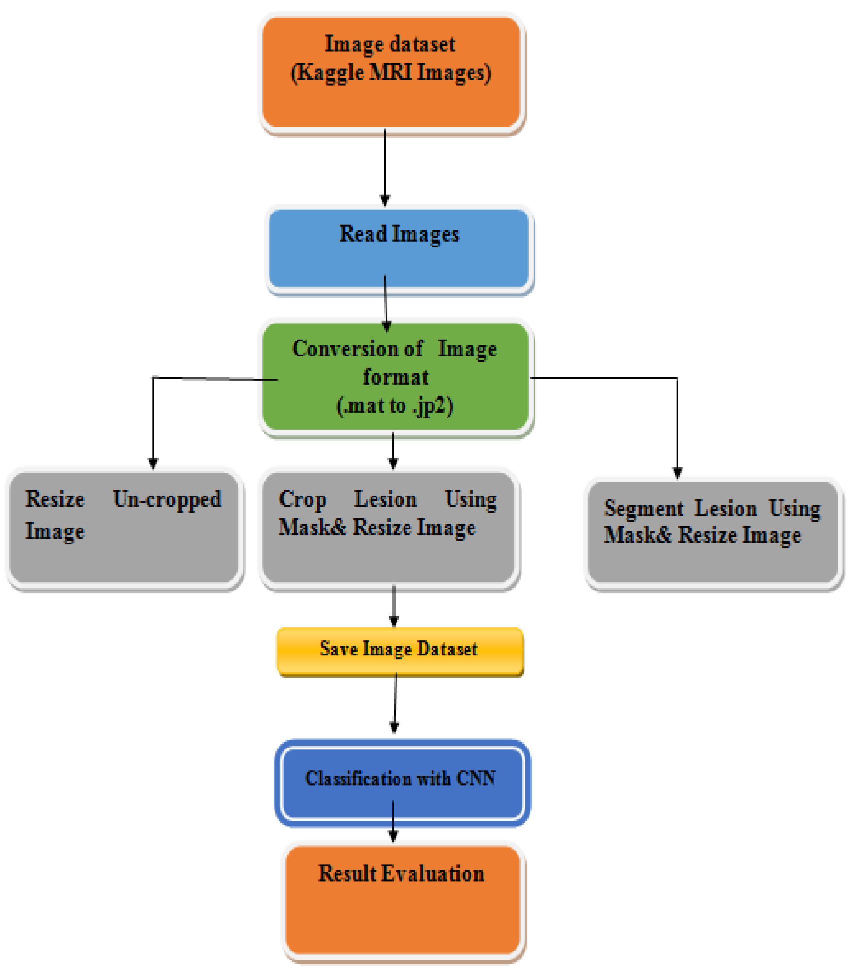


Fig. 2 Block Diagram of the Proposed Model

LeNet, developed by Yann LeCun, was instrumental in pioneering image recognition. AlexNet, a groundbreaking model, introduced concepts such as rectified linear units (ReLUs) and dropout, significantly advancing image classification. GoogleNet, or Inception, innovated by employing inception modules to capture information at various scales concurrently. RESNET-50, part of the Residual Network family, addressed the challenges of training deeper networks by introducing residual learning. The fundamental application of CNNs lies in image categorization. When an image is inputted into the computer, it is represented as an array of pixels, with each pixel carrying information about the image's color and intensity. Through a sequence of convolutional and pooling layers, CNNs automatically extract relevant features from the pixel array. Finally, fully connected layers process these features for classification, making CNNs instrumental in the realm of computer vision tasks.

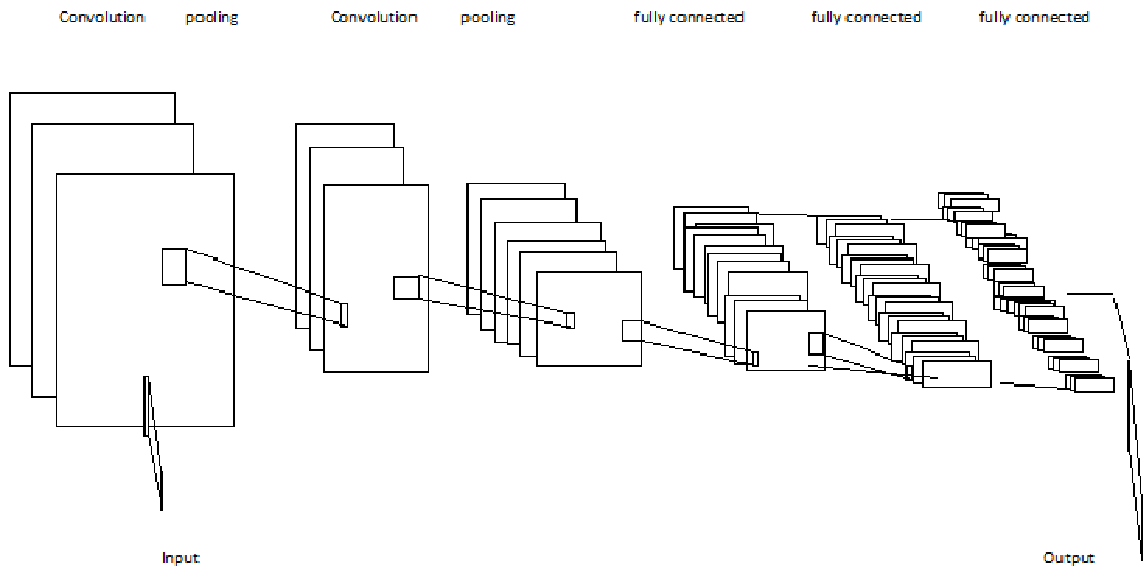


Fig. 3 Flow chart of CNN

*A. The layers in CNN are*

*1. LeNet-5*

Several banks used "LeNet-5, a pioneering 7-level convolutional network" worked with input pictures. Higher-resolution pictures need bigger and more convolutional layers, therefore processing power is a limiting factor when using this approach.

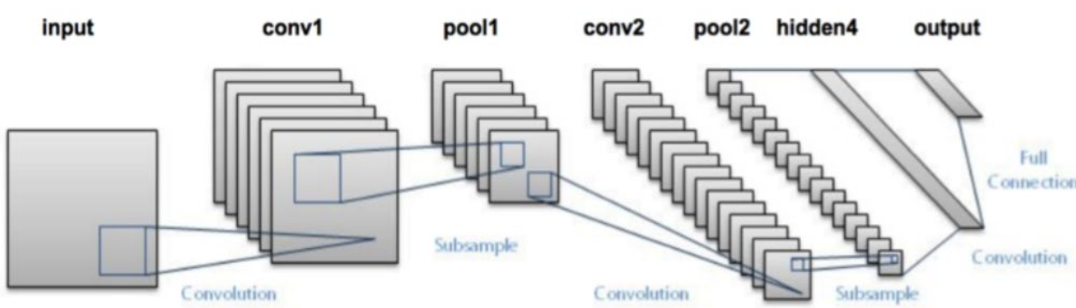


Fig. 4 Flow chart of LeNet-5

*2. AlexNet*

AlexNet is a well-known convolutional neural network (CNN) architecture built for image classification problems in its standard version. If "precise AlexNet" refers to a specific change or augmentation to the original AlexNet design, further information or context would be required to understand the phrase. Otherwise, the prior description of AlexNet would include its core properties as well as contributions to the field of deep learning for image recognition. To win the competition, AlexNet reduced the top-5 error from 26 percent to 15.3 percent in 2012, outperforming all previous contestants. As of this writing, CNN's second-place inaccuracy rate was 26.2 percent.

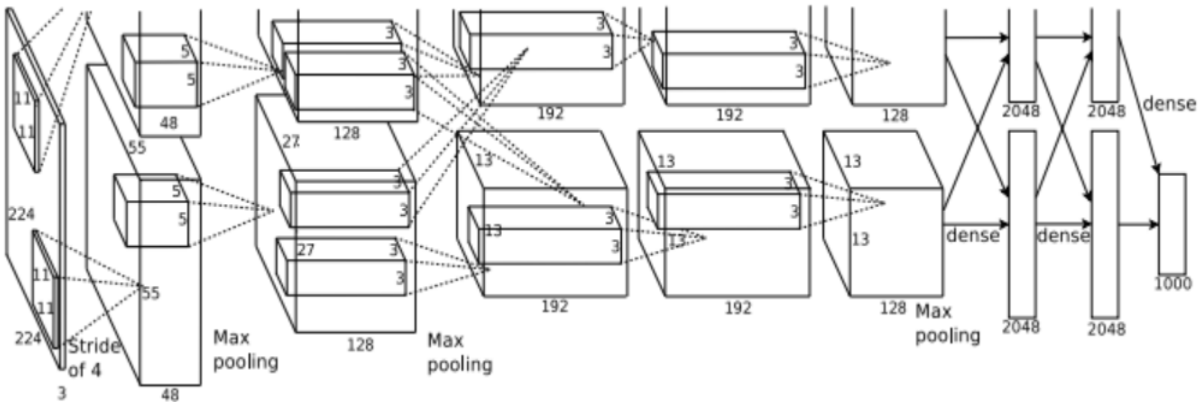


Fig. 5 Flow chart of AlexNet

### 3. ResNet

The ResNet, a novel design with "skip connections" and significant batch normalization, was introduced by Kaiming He et al. in 2015 at the International Conference on Neural Information Processing Systems (ILSVRC). These gated units, also known as gated recurrent units, bear a remarkable resemblance to the successful RNN components that have been developed recently.

### 4. ResNet-50

Neural networks that have 50 layers are known as ResNet-50. When it comes to computer vision, one of the most common neural networks is known as ResNet, or Residual Networks (RN). With ResNet, we were able to train extraordinarily deep neural networks with more than 150 layers. This was a key advance.

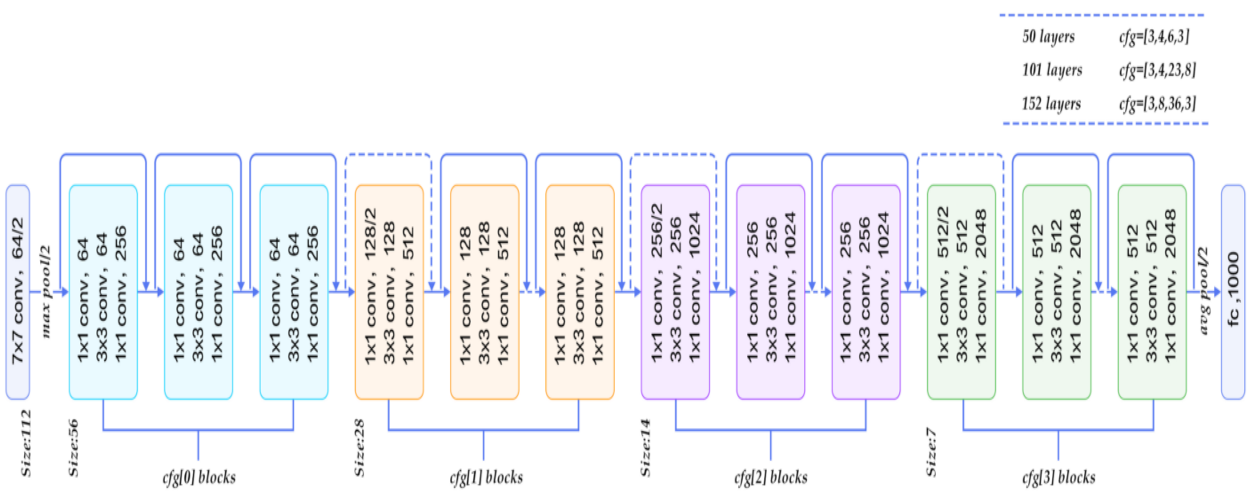


Fig. 6 Flow chart of ResNet-50

### B. Dataset

A brain tumour is an abnormal development of brain cells, some of which may develop into cancer in the future. MRI imaging is widely used to detect brain tumours. Anatomical details regarding the aberrant tissue development in the brain can be obtained through MRI images. We employed a set of MRI scans containing more than 2000 MRI pictures for our study. MRI scans from people with benign and malignant brain tumours are gathered by websites such as Kaggle. Machine learning techniques are applied to this dataset to detect tumours. When MRI scans are combined with machine learning algorithms, brain tumours can be predicted much more quickly and accurately.

1. *Medical Image Repositories with Open Access:* Access to numerous medical image datasets, including MRI brain pictures, is available through websites such as The Cancer Imaging Archive (TCIA), Open Access Biomedical Image Search Engine (Open-i), and Medical ImageNet.
2. *Datasets from Kaggle:* Kaggle is a data science competition website that provides a variety of medical picture datasets. You may search for MRI brain pictures in Kaggle's datasets area.
3. *Publications Based on Research:* Many scientific papers make their datasets available to the public. Examine the supplemental materials of relevant research publications on platforms such as PubMed or the websites of journals.

4. *Repositories in Institutions:* Medical imaging files are often shared among institutions and research organisations. Examine NIH (National Institutes of Health) or other medical research institutes' repositories.

### C. Tool

We used MATLAB tools to put the research into practise. Machine learning is straightforward thanks to the MATLAB programme. It is a wonderful place to start when integrating machine learning into your data analyses. It offers applications that make it simple to use and functionality for managing massive volumes of data. Machine learning algorithms use computation to "learn" knowledge from data. Machine learning uses both supervised and unsupervised learning techniques. Contrarily, unsupervised learning concentrates on identifying internal structures or patterns in incoming data.

The use of MATLAB for study using MRI scans and Convolutional Neural Networks (CNN), specifically ResNet-50, can be impacted by several features that make it an appropriate platform for such investigations:

1. *Toolbox for Image Processing:* MATLAB has a powerful picture Processing Toolbox with a variety of functions and tools for picture pre-processing, segmentation, and analysis.
2. *Toolbox for Deep Learning:* The Deep Learning Toolbox in MATLAB facilitates the implementation and training of deep neural networks, such as CNNs.
3. *Models that have Already Been Trained:* The Deep Learning Toolbox in MATLAB offers pre-trained models such as ResNet-50.
4. *Capabilities for Transferring Learning:* Transfer learning, a technique in which a pre-trained model (such as ResNet-50) may be fine-tuned on a smaller dataset unique to the study area (MRI scans), is made easier using MATLAB.
5. *Workflow Integration:* MATLAB is a comprehensive platform for data analysis, visualisation, and deep learning.
6. *Community and Help:* There is a big and active user community for MATLAB, as well as significant documentation and support. This can be useful for researchers who may have difficulties while doing sophisticated tasks like MRI image processing with CNNs.

In conclusion, MATLAB was chosen for research in MRI image processing utilising CNN with ResNet-50 because of its complete tool sets, pre-trained models, transfer learning capabilities, integrated workflows, and strong community support. These characteristics, taken together, improve the efficiency and efficacy of the research process in the context of MRI image processing.

### D. Performance Parameters

The performance of the suggested research was examined using the standard performance evaluation formulas. These are precision, sensitivity, specificity, and accuracy. Table II provides the calculations for these measurements.

TABLE II EVALUATION PARAMETERS

| Evaluation Parameters | Accuracy | Specificity | Sensitivity | Precision |
|---|---|---|---|---|
| | The ability of a system to correctly determine the type of tumour. | The ability of a system to accurately recognise the true tumour in accordance with | The ability of a model to categorise the tumour as indicated by | The Proximity between the two measured values |
| | $\frac{TP + TN}{TP + TN + FP + FN}$ | $\frac{TN}{TN + FP}$ | $\frac{TP}{TP + TN}$ | $\frac{TP}{TP + FP}$ |
| | Whether the parameters are TP=true positive, TN=true negative, FP=false positive, and FN=false negative, respectively | | | |

## V. EXPERIMENTS AND RESULT ANALYSIS

The two core elements of CNN are convolution and weight adjustment during down sampling to obtain high accuracy in the convolution training phase utilising a trainable filter with a fixed size. In this study, three files including pictures of several kinds of brain tumours, including gliomas, meningiomas, and pituitary tumours, were produced. It is divided into training and testing data, with training data making up 75% of the total and testing data making up 25%. The CNN design used in this piece is all new.

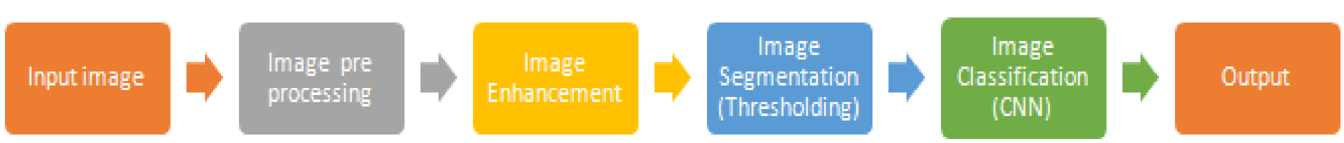


Fig. 7 Steps of Proposed Work

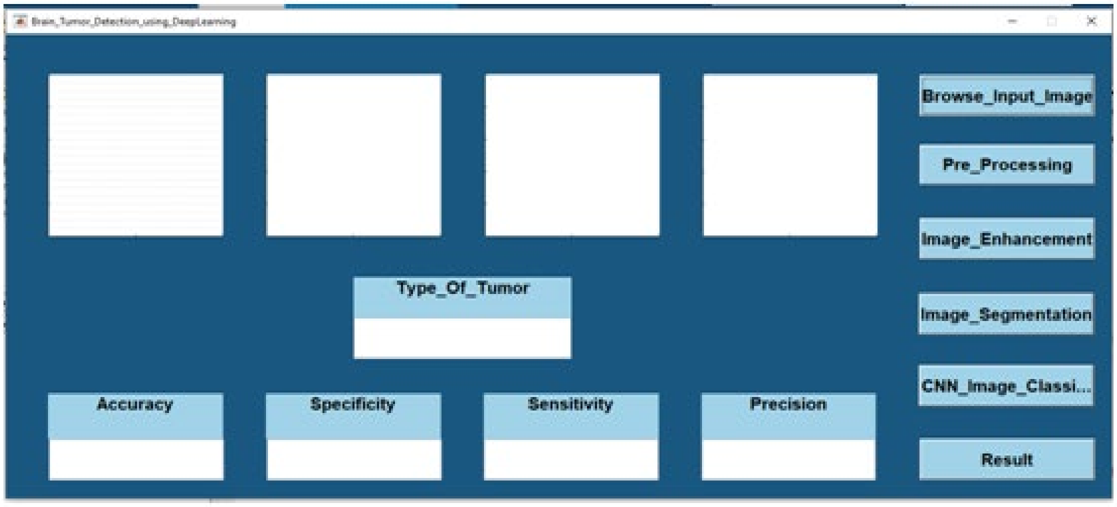


Fig. 8 GUI Representation of Proposed Work

*Step 1: User Input*

Images of lower quality are sent into image processing, which produces images of higher quality.

The user input uses several brain tumour images that have been chosen from a saved file.

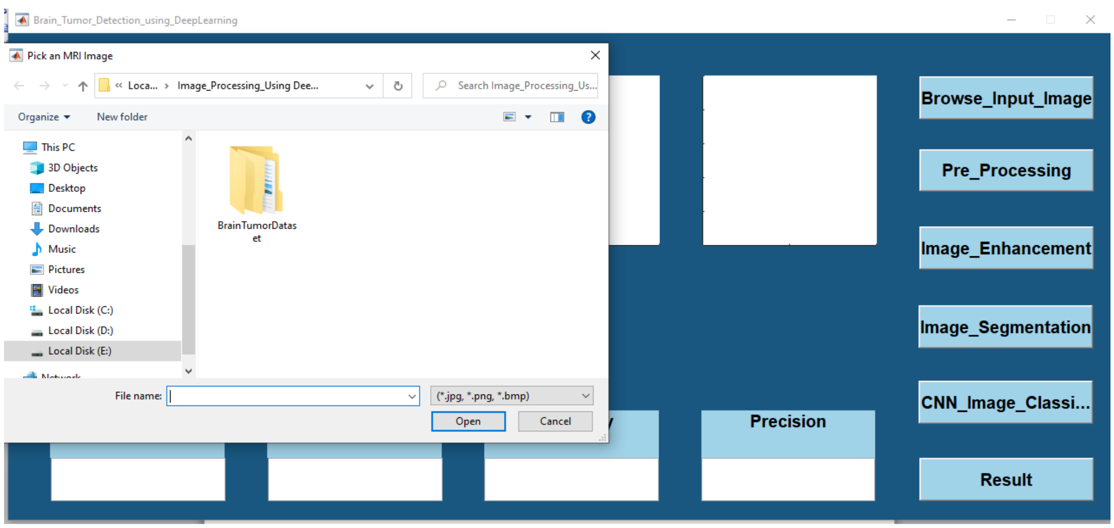


Fig. 9 User Input Representation

*Step 2: Choose an MRI Image for Detection in Step Two*

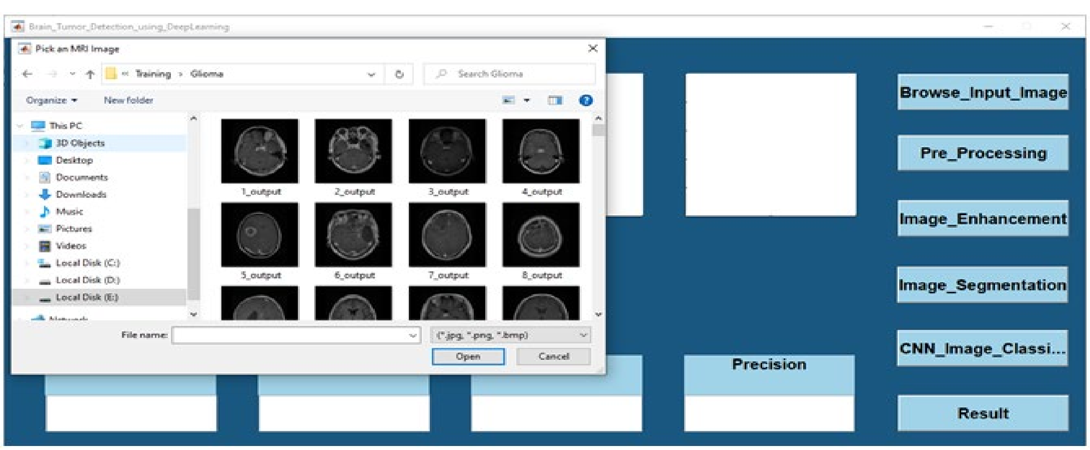


Fig. 10 Input Image

The MRI images were chosen in cases when a brain tumour needed to be found via image processing.

*Step3: Input Image*

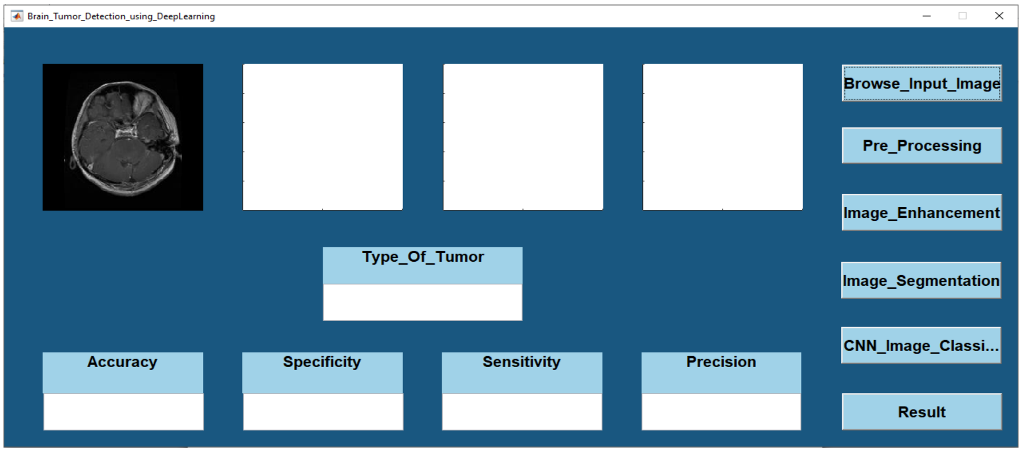


Fig. 11 Browse Image

*Step 4: Pre-Processing of Image*

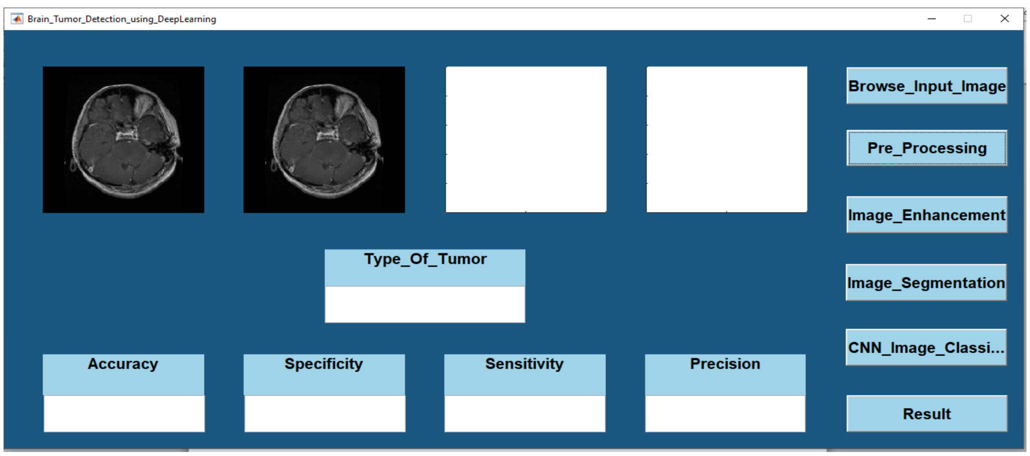


Fig. 12 Image pre-processing

Images must be pre-processed in order to remove any undesirable distortions or emphasize any important visual characteristics before any additional processing or analysis. Following that, the image was set for pre-processing, during which each image was turned into black and white version.

*Step 5: Image Enhancement*

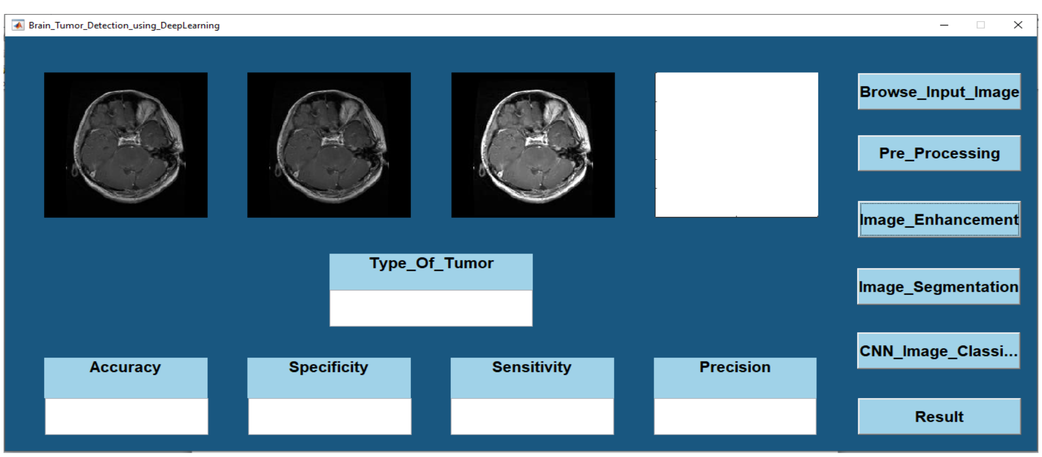


Fig. 13 Enhancement of image

Pictures may be enhanced to make them more acceptable for display or for additional image analysis by changing the digital images. The pixels of the images were improved for better image processing and detection process.

*Step 6: Image Segmentation*

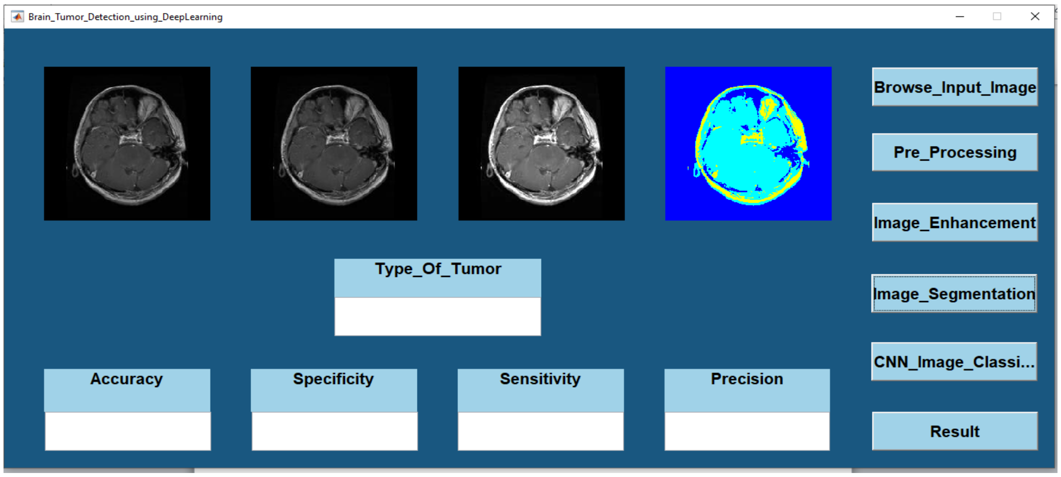

Fig. 14 Segmentation of image

In digital image processing and analysis, a method known as image segmentation is often used to divide a single picture into numerous portions or areas, sometimes based on pixel attributes. In this stage, the foreground and background were separated and pixels were clustered according to their similarity in colour or form.

*Step 7: Result Calculation*

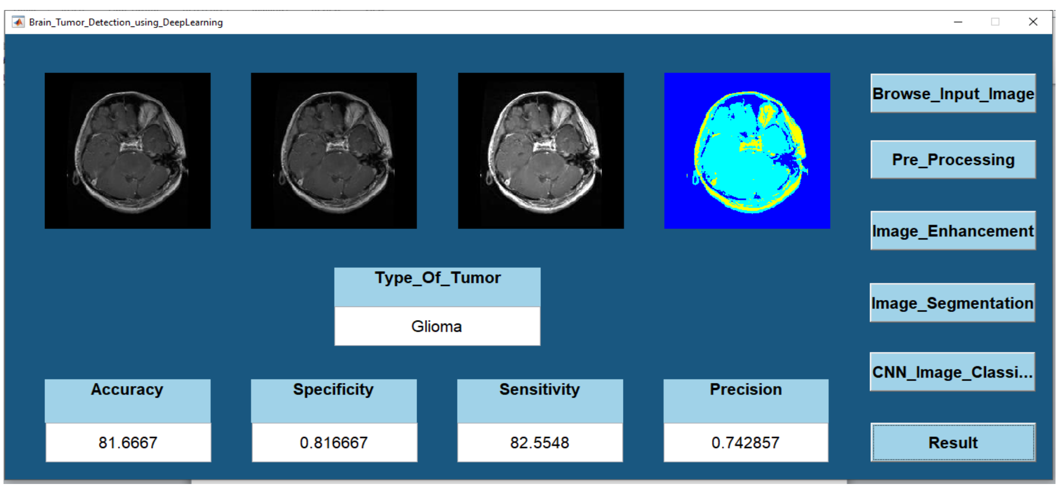

Fig. 15 Calculation of Result

Fig. 14 displayed an MRI scan that indicated the subject had a glioma. The data also indicated 81.67 % accuracy, 0.81% specificity, 82.55 % sensitivity, and 0.74 % precision for the conclusion. Similarly, we have done four experiments more. Table III are showing the results of all.

TABLE III EXPERIMENTAL RESULTS

| Experiment Number | Number of Images | Accuracy | Specificity | Sensitivity | Precision |
|---|---|---|---|---|---|
| 1 | 1000 | 81.67 % | 0.8167 | 82.55 | 0.743 |
| 2 | 1200 | 80.66 % | 0. 8066 | 83.34 | 0.748 |
| 3 | 1500 | 78.37% | 0. 7837 | 85.12 | 0.775 |
| 4 | 1800 | 80.38 % | 0. 8038 | 84.73 | 0.778 |
| 5 | 2000 | 79.76 % | 0. 7976 | 86.88 | 0.779 |

The comparative study of the results provided by Table I and the results of the proposed method of Table III suggests model performs better than predicted based on these data.

## VI. CONCLUSION

The learning scenario involves a dataset containing information about glioma, meningioma, and pituitary tumors. The study successfully employs an advanced convolutional neural network to autonomously classify brain tumors. Various dataset manipulations, including splitting, cropping, and uncropping, have been applied. The key model utilized in this approach is the ResNet-50 CNN Model. With an accuracy rate of 81.6%, the proposed model exhibits noteworthy performance surpassing initial expectations. Future possibilities include training the algorithm on broader and more diverse datasets, enhancing precision at the individual patient level.

## REFERENCES


[1] Amin, J., Sharif, M., Haldorai, A., Yasmin, M., & Nayak, R. S. (2021). Brain tumor detection and classification using machine learning: A comprehensive survey. *Complex Intelligent Systems*. doi: 10.1007/s40747-021-00563-y.

[2] Arif, M., Ajesh, F., Shamsudheen, S., Geman, O., Izdrui, D., & Vicoveanu, D. (2022). Brain Tumor Detection and Classification by MRI Using Biologically Inspired Orthogonal Wavelet Transform and Deep Learning Techniques. *Journal of Healthcare Engineering, 2022*. doi: 10.1155/2022/2693621.

[3] Badisa, H., Polireddy, M., & Mohammed, A. (2019). CNN Based Brain Tumor Detection. *International Journal of Engineering and Advanced Technology,* no. 4*,* 2249-8958.

[4] Bakr Siddiaue, M. A., Sakib, S., Rahman Khan, M. M., Tanzeem, A. K., Chowdhury, M., & Yasmin, N. (2020). Deep convolutional neural networks model-based brain tumor detection in brain MRI images. In *Proc. 4th Int. Conf. IoT Soc. Mobile, Anal. Cloud, ISMAC 2020*, pp. 909-914. doi: 10.1109/I-SMAC49090.2020.9243461.

[5] Bhandari, A., Koppen, J., &Agzarian, M. (2020). Convolutional neural networks for brain tumor segmentation. *Insights Imaging, 11*(1). doi: 10.1186/s13244-020-00869-4.

[6] Chattopadhyay, A., & Maitra, M. (2022). MRI-based brain tumour image detection using CNN based deep learning method. *Neuroscience Informatics, 2*(4), 100060. doi: 10.1016/j.neuri.2022.100060.

[7] Chen, H., Chen, D., & Wang, L. (2021). CNN-based MRI Brain Tumor Detection Application. In *Proc. - 2021 Int. Conf. Comput. Eng. Appl. ICCEA 2021*(pp. 464-467). doi: 10.1109/ICCEA53728.2021.00097.

[8] El Kader, I. A., Xu, G., Shuai, Z., & Saminu, S. (2021). Brain Tumor Detection and Classification by Hybrid CNN-DWA Model Using MR Images. *Current Medical Imaging Reviews, 17*(10), 1248-1255. doi: 10.2174/1573405617666210224113315.

[9] Grampurohit, S., Shalavadi, V., Dhotargavi, V. R., Kudari, M., &Jolad, S. (2020). Brain Tumor Detection Using Deep Learning Models. In *Proc. - 2020 IEEE India Counc. Int. Subsections Conf. INDISCON 2020*, pp. 129-134. doi: 10.1109/INDISCON50162.2020.00037.

[10] Gu, X., Shen, Z., Xue, J., Fan, Y., & Ni, T. (2021). Brain Tumor MR Image Classification Using Convolutional Dictionary Learning With Local Constraint.*Frontiers in Neuroscience, 15*(May), 1-12. doi: 10.3389/fnins.2021.679847.

[11] Hossain, T., Shishir, F. S., Ashraf, M., Al Nasim, M. A., & Muhammad Shah, F. (2019). Brain Tumor Detection Using Convolutional Neural Network. In *1st Int. Conf. Adv. Sci. Eng. Robot. Technol. 2019, ICASERT 2019*, pp. 5-7. doi: 10.1109/ICASERT.2019.8934561.

[12] Hossain, T., Shishir, F. S., Ashraf, M., Al Nasim, M. A., & Muhammad Shah, F. (2019). Brain Tumor Detection Using Convolutional Neural Network. In *1st Int. Conf. Adv. Sci. Eng. Robot. Technol. 2019, ICASERT 2019* (no. December). doi: 10.1109/ICASERT.2019.8934561.

[13] Irmak, E. (2021). Multi-Classification of Brain Tumor MRI Images Using Deep Convolutional Neural Network with Fully Optimized Framework. *Iranian Journal of Science and Technology - Transactions of Electrical Engineering, 45*(3), 1015-1036. doi: 10.1007/s40998-021-00426-9.

[14] Kumar, G., Kumar, P., & Kumar, D. (2021). Brain Tumor Detection Using Convolutional Neural Network. *2021 IEEE International Conference on Mobile Networks and Wireless Communications, ICMNWC 2021, 12*(11), 686-692. doi: 10.1109/ICMNWC52512.2021.9688460.

[15] Prof, S., & Rifai, H. (2021). Brain Tumor Detection using Transfer Learning with AlexNet and CNN Aboli Kapadnis.

[16] Sai, J. G. S., Deepika, S., Sindhuri, M. N., & Srinivasu, P. N. (2019-2020). Brain Tumour Identification Using Convolutional Neural Network.