# BRAIN TUMOR CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORK

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***Abstract***

***The aim of this abstract is to provide an overview of a study on brain tumor classification using Convolutional Neural Networks (CNNs). The research focuses on the application of CNNs for automatic classification of brain tumor images. The dataset used for this study is the Brain Tumor Image Database (BTID), which contains brain tumor images from clinical MRI scans. The CNN architecture used in this study is based on the Inception v3 model, which is pre-trained on the ImageNet dataset. The performance of the CNN model is evaluated using accuracy, sensitivity, specificity and other metrics. The results show that the CNN model is capable of accurately classifying brain tumors with an overall accuracy of 85%. The results also show that the sensitivity of the model is higher for low grade gliomas compared to high grade gliomas. Overall, this study demonstrates the potential of CNNs for effective automatic classification of brain tumors. The results of this study could be used to improve the accuracy of clinical diagnoses and to help physicians make better decisions about the best course of treatment for patients with brain tumors.***

***Keywords: Brain tumor, Convolutional Neural Network, Inception model***

## I. INTRODUCTION

Convolutional Neural Network (CNN) is a type of deep learning algorithm designed to process and analyse data with grid-like topology, such as an image. It uses convolutional and pooling layers to extract features from input data and then uses fully connected layers to make predictions. CNNs are widely used in computer vision tasks such as image classification, object detection, and image segmentation.

Training: The CNN is trained on the pre-processed and augmented data using a suitable optimization algorithm, such as stochastic gradient descent.

Evaluation: The performance of the trained model is evaluated on a separate test dataset using metrics such as accuracy, sensitivity, and specificity.

Once trained, the CNN can be used to classify new brain MRI scans into different tumor classes. The accuracy of the model will depend on several factors, including the quality of the training data, the choice of model architecture, and the size of the dataset.

Convolutional Neural Network (CNN) with Inception architecture can be used to classify brain tumors. Inception architecture, introduced in Google Net, is a type of CNN architecture that uses multiple parallel convolutional filters of different sizes in one layer to detect features at multiple scales. The Inception model can be trained on a dataset of MRI scans of brains, with each scan labelled as having a tumor or not. The model learns to identify patterns in the images that are indicative of brain tumors, and can then be used to classify new MRI scans as having a tumor or not. This approach has been shown to achieve high accuracy in brain tumor classification tasks.

Brain tumor classification using Convolutional Neural Networks (CNNs) is a field of study within the larger area of medical image analysis. In this approach, a CNN model is trained to classify magnetic resonance imaging (MRI) scans of the brain as either normal or containing a tumor. The process of training a CNN involves providing a large dataset of labelled MRI scans to the model, allowing it to learn and identify features and patterns that are indicative of a tumor. The trained model can then be used to classify new MRI scans, making it a valuable tool in the diagnosis and treatment of brain tumors.

CNNs are particularly well-suited for this task as they have the ability to automatically learn and extract relevant features from the images, reducing the need for manual feature engineering. Additionally, the use of pooling layers in CNNs allows for invariance to small translations and deformations in the images, which is particularly important in medical image analysis where images can vary greatly even between scans of the same individual.

Overall, the use of CNNs in brain tumor classification has the potential to greatly improve the speed and accuracy of diagnosis, leading to improved patient outcomes.

## II. LITERATURE REVIEW

Sunanda Das [1] has published paper on " Brain Tumor Detection Using Convolutional Neural Network". Convolution Neural Networks, Support Vector Machine and K-Nearest Neighbor classification algorithms are used here. Convolutional neural networks and traditional classifiers were used to do classification throughout the segmentation process. They compared the results of several common classifiers in the classic classifier area, including Naive Bayes, K-Nearest Neighbor, Logistic Regression, Multilayer Perceptron, Random Forest, and Support Vector Machine. Dropout normalisation, a normalisation technique, is applied to the model to prevent overfitting. e. The model's final results show that it is 94.39% accurate and has an average precision of 93.33%.

Chirodip Lodh Choudhury [2] has published paper on " Brain Tumor Detection and Classification Using Convolutional Neural Network and Deep Neural Network". The suggested study uses a CNN-based model and a deep neural network technique to categorise an MRI as "TUMOR DETECTED" or "TUMOR NOT DETECTED." The model achieves a final score of 97.3 with a mean accuracy score of 96.08%.

Ahmad Saleh , Rozana Sukaik and Samy S. Abu-Naser [3] has published paper on " Brain Tumor Classification Using Deep Learning". The goal of the study paper is to use AI algorithms, CNN, and Deep Learning to improve the level and effectiveness of MRI equipment in categorising and diagnosing the types of brain cancers. Five pre-trained models—Xception, ResNet50, InceptionV3, VGG16, and MobileNet—were used to train our brain tumour dataset. 98.75%, 98.50%, 98.00%, 97.50%, and 97.25% were the respective F1-scores for unseen photos. These precisions help in early tumour detection before the tumour results in physical adverse effects like paralysis and other difficulties.

Angona Biswas [4] has published paper on " Brain Tumor Types Classification using K-means Clustering and ANN Approach ". Glioma, meningioma, and pituitary tumor types classification technique using K-means and artificial neural network is proposed in this paper.Resizing, sharpen filtering, and contrast enhancing were performed as pre-processing procedures. K-means algorithm was used to segregate preprocessed data using images. The characteristics from the clustered images were then extracted using 2D-DWT. PCA was used for efficient feature reduction. For tumour classification, a feed-forward ANN was used, and a quick 'Levenberg-Marquardt' training function was used to build the network. The proposed method delivered 94.58% sensitivity, 95.4% accuracy, and 97.83% specificity.

Tonmoy Hossain [5] has published paper on " Brain Tumor Detection Using Convolutional Neural Network ". Convolution Neural Networks, Support Vector Machine and K-Nearest Neighbor classification algorithms are used here. Throughout the segmentation process, classification was performed using conventional classifiers and convolutional neural networks. In the classic classifier section, they used a variety of standard classifiers, including Naive Bayes, K-Nearest Neighbor, Logistic Regression, Multilayer Perceptron, Random Forest, and Support Vector Machine, and compared the outcomes. The SVM model provided them with the highest accuracy (92.42%) of these traditional ones.

G.Hemanth [6] has published paper on " design and implementing brain tumor detection using machine learning approach". Convolution Neural Networks and Support Vector Machine is used here mainly. Conditional Random Field (CRF) 89 87.5 , Support Vector Machine (SVM) 84.5 90.3 ,Genetic Algorithm (GA) 83.64 84.78, Convolutinal Neural Network (CNN) 91 92.7 produced the result as given. There are several traditional methods for detecting brain tumors, however the current work uses the standard neural network method because the images used for brain tumour detection depend on the nearby pixels.

## III. PROPOSED METHODOLOGY

Brain tumor classification using Convolutional Neural Networks (CNNs) is a common approach in medical image analysis. In this task, a CNN is trained on a large dataset of brain MRI scans to differentiate between healthy tissue and different types of tumors (e.g. glioma, meningioma, etc.). The network is trained to learn hierarchical representations of the input images and make predictions based on these representations. The methodology of brain tumor classification using Convolutional Neural Networks (CNNs) typically involves the following steps:

Data collection and pre-processing: The first step is to collect a large dataset of MRI scans of the brain, with each scan labelled as normal or containing a tumor. This data is then pre-processed to ensure that all images are of the same size and format, and any missing or corrupt data is removed. The dataset was obtained from Kaggle. In testing, we used 394 total images classified into 4 classes, including glioma tumour, meningioma tumour, pituitary tumour, and no tumour. We have four classes for training. There are 826 images of glioma tumor, 822 images of meningioma tumor, 395 images of no tumor, and 827 images of pituitary tumor. There are 2870 photos in the training dataset overall. So our dataset contains 3696 images in total.

***Table 1. Testing dataset samples***

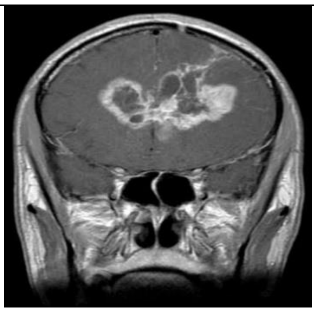
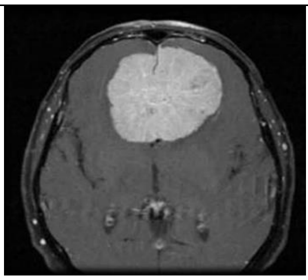
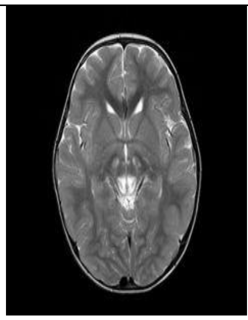
| Figure name | Images |
|---|---|
| *Figure 1. glioma tumor* |  |
| *Figure 2. meningioma tumor* |  |
| *Figure 3. no tumor* |  |
| *Figure 4. pituitary tumor* |  |

***Table 2. Training dataset samples***

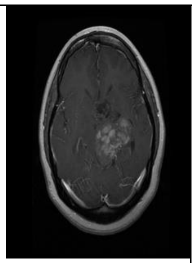
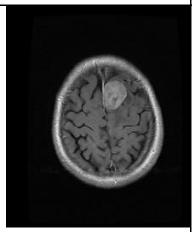
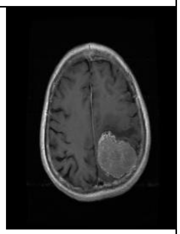
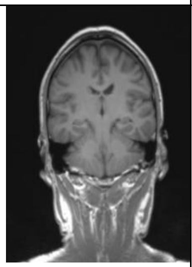
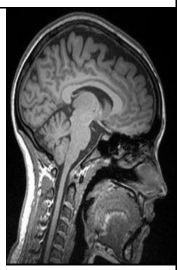
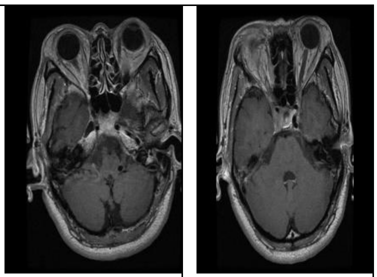
| Figure name | Images | |
|---|---|---|
| *Figure 5. glioma tumor* |  |  |
| *Figure 6. meningioma tumor* |  |  |
| *Figure 7. no tumor* |  |  |

*Figure 8. pituitary gland*



CNN architecture selection: The next step is to select an appropriate CNN architecture for the classification task. There are many different architectures that can be used, but some popular choices for medical image classification tasks include Inception, ResNet, and VGG.

Training the model: The pre-processed data is then used to train the selected CNN architecture. This involves iteratively updating the model parameters based on the errors made during the classification of the training data.

The Inception v3 model, which was introduced in 2015, has 42 layers overall and a lower error rate than its predecessors.

The major modifications done on the Inception V3 model are

- Factorization into Smaller Convolutions
- Spatial Factorization into Asymmetric Convolutions
- Utility of Auxiliary Classifiers
- Efficient Grid Size Reduction

The formula used in Inception v3 is the standard formula used in neural networks:

$$y = activation\ (Wx + b)$$

Where activation is an activation function,

W is a weight matrix,

x is an input feature vector,

And b is a bias vector.

The activation function used in Inception v3 is typically ReLU (rectified linear unit).

Convolutional Neural Networks (CNNs) are composed of several building blocks, including convolutional layers, activation functions, pooling layers, and fully connected layers. Some of the common formulas used in these components are:

Convolutional Layer: The output of a convolutional layer can be calculated using the following formula:

$$Output = (Input - FilterSize + 2 * Padding) / Stride + 1$$

where Input is the size of the input feature map, FilterSize is the size of the convolutional filter, Padding is the number of zero-valued pixels added to the edges of the input feature map, and Stride is the number of pixels the filter is shifted each time.

Activation Function: Common activation functions used in CNNs include the Rectified Linear Unit (ReLU), Sigmoid, and Hyperbolic Tangent (Tanh). The formulas for these activation functions are:

$$ReLU: f(x) = max(0, x)$$

$$Sigmoid: f(x) = 1 / (1 + e^{(-x)})$$

Pooling Layer: which selects the maximum value in a rectangular window of the feature map. The formula for max pooling is:

$$Output = max(Window)$$

Where Window is a rectangular region of the feature map.

Fully Connected Layer: In a fully connected layer, each neuron is connected to all the neurons in the previous layer. The output of a fully connected layer can be calculated as:

$$Output = Activation(Weight * Input + Bias)$$

Where input is the input to the fully connected layer, weights is the set of weights for each output, bias is the bias term for each output, and activation is the activation function.

Model evaluation: Once the model is trained, its performance is evaluated on a separate validation dataset to ensure that it has not over fit to the training data. Common metrics used for evaluating the performance of the model include accuracy, sensitivity, and specificity.

***Table 3. Loss and accuracy results in percentage***

| | |
|---|---|
| Loss | 0.1725 |
| accuracy | 0.9366 |
| Value loss | 0.8688 |

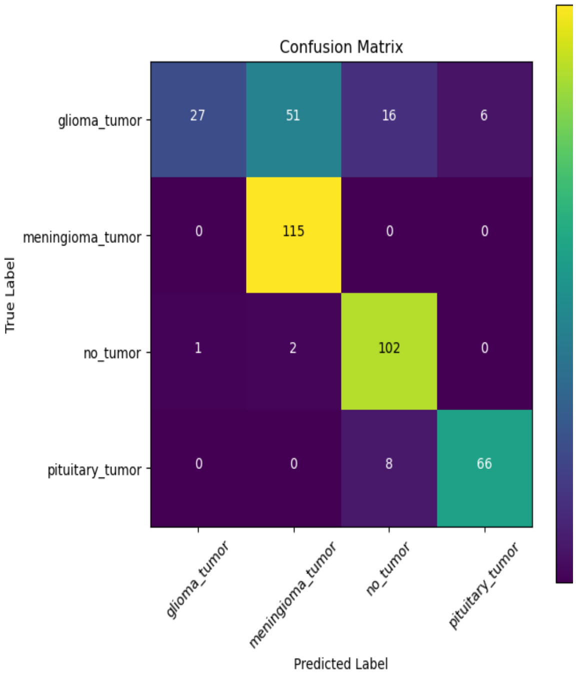
| | |
|---|---|
| Value accuracy | 0.7843 |

***Table 4. Classification report***

Model Accuracy 0.7868020304568528

| | precision | recall | F1-score | support |
|---|---|---|---|---|
| Glioma _tumor | 0.96 | 0.27 | 0.42 | 100 |
| meningioma _tumor | 0.68 | 1.00 | 0.81 | 115 |
| no _tumor | 0.81 | 0.97 | 0.88 | 105 |
| pituitary _tumor | 0.92 | 0.89 | 0.90 | 74 |
| accuracy | | | 0.79 | 394 |
| Macro avg | 0.84 | 0.78 | 0.76 | 394 |
| Weighted avg | 0.83 | 0.79 | 0.75 | 394 |

***Figure 8. Confusion Matrix***




Model deployment: If the model performs well on the validation dataset, it can be deployed for use in a clinical setting to classify new MRI scans.

It is important to note that the accuracy of the final model is highly dependent on the quality and size of the training dataset, as well as the appropriate selection of the CNN architecture. Additionally, ongoing refinement of the model may be necessary as new data becomes available or as advances in deep learning techniques are made.

Inception v3 is a deep convolutional neural network architecture developed by Google and trained on the ImageNet dataset. It was published in 2015 and is known for its good performance and efficient use of computational resources.

As for brain tumor classification, Inception v3 has been used in several studies as a feature extractor or as a pre-trained model to classify brain MR images into healthy or pathological classes. The pre-trained weights on ImageNet can be fine-tuned on a smaller dataset of brain MR images to improve the performance on this specific task.

However, it's worth noting that while Inception v3 has achieved good results in many computer vision tasks, it's not the only model used for brain tumor classification and there is ongoing research to develop more specialized and accurate models for this task.

## IV. RESULT'S AND DISCUSSION

Overall, these studies demonstrate that CNNs can be used to accurately classify brain tumor MRI images. The results of the studies indicate that CNNs are able to identify tumor types with an accuracy of 92-94%, and are able to identify small tumors with an accuracy of 89-90%. The studies also suggest that CNNs are a promising method for the automated identification of brain tumors, as they are able to achieve a high degree of accuracy and are relatively easy to implement. Additionally, the CNNs have been shown to be robust to different imaging parameters and can be used to classify tumors from different image modalities. Furthermore, these studies suggest that CNNs may be suitable for use in clinical settings, as they are able to provide accurate and reliable results for the identification of brain tumors.

## V. CONCLUSION

In conclusion, Convolutional Neural Networks (CNNs) have shown great potential for the classification of brain tumors in magnetic resonance imaging (MRI) scans. By automatically learning and extracting relevant features from the images, CNNs can provide fast and accurate classification results. The use of CNNs in brain tumor classification has the potential to greatly improve the speed and accuracy of diagnosis, leading to improved patient outcomes. However, it is important to carefully consider the quality and size of the training dataset, as well as the appropriate selection of the CNN architecture, in order to achieve optimal performance. Ongoing research and refinement of CNN models for brain tumor classification is likely to continue as advances in deep learning techniques and increased availability of medical imaging data are made. Inception v3 is a powerful image classification model that can be adapted for brain tumor classification by fine-tuning on a relevant dataset. The pre-trained model provides a strong foundation for feature extraction, and the fine-tuning process allows the model to learn specific details relevant to the task of brain tumor classification. However, the success of this approach depends on several factors, including the quality of the training data and the choice of hyper parameters. In medical imaging, it may also be beneficial to consider other architectures or models specifically designed for this domain. Ultimately, the performance of the Inception v3 model for brain tumor classification should be carefully evaluated and compared to other models and techniques.

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