Module	**Report Topic**
Complex System (6CS041)	Brain Cancer Detection using CNN

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Table of Contents

1. Introduction 1

2. Aim & Objectives 2

2.1. Aim 2

2.2. Objectives 2

3. Literature review 2

4. Analysis and Findings 6

5. Conclusion 9

6. References 10

Table of Figures

Figure 1: Brain Tumor Segmentation Approach 3
Figure 2: Training and validation accuracy curve **&** Evaluation metric score of proposed model 4
Figure 3: Methodology using MobileNet 5
Figure 4: CNN Model Architecture 6
Figure 5: Precision Formula 6
Figure 6: Recall Formula 7
Figure 7: Specificity Formula 7
Figure 8: F1-Score Formula 7
Figure 9: Comparison of different methods implemented 8

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Abstract

Brain cancer is a serious and often fatal disease that affects millions of people worldwide. Early detection of brain cancer is crucial for successful treatment, and advances in technology have made it possible to use convolutional neural networks (CNNs) for detection. In this study, we evaluated the performance of various CNN models for detecting brain tumors in medical imaging scans. We evaluated the training of multiple CNNs on a large dataset of brain scans and evaluated the comparison of their performance in detecting brain tumors. Our finding showed that different CNN models can have varying levels of accuracy in detecting brain tumors, and that some models are more effective than others. We also found that fine-tuning the parameters of the CNNs can improve their performance, and that assembling multiple CNNs can further improve their accuracy. Our findings suggest that the use of different CNN models and techniques can improve the accuracy and speed of brain cancer detection, ultimately leading to better outcomes for patients.

1. Introduction

Brain cancer (tumor) occurs when there is excessive growth of cells in the brain. The structure is very complex compared to other part of the body as it is responsible for different functions of nervous system. And brain tumor can occur in any part of the skull or the brain. There are more than 120 kinds of tumor which can arise depending on the tissue.

This cancer is one of the most vital and dangerous cancer around the world. In 2020, around 308,102 people were diagnosed with brain cancer. The death rate is also very high as it is second cause of death after breast cancer. And early treatment of brain cancer can be a major factor in reducing the mortality rate and can help to recover from cancer.

For, the early diagnosis and detection of brain cancer, different techniques are implemented. For example, image modalities are now very popular among the radiologist as they provide less risk to patient and are more accurate. Radiography, Tomography, Echocardiography and Magnetic Resonance Imaging (MRI) are some of the most used methods for capturing medical imaging data. And among them, MRI provides the most prominent images with high resolution.

Nowadays, Computer-Aided Diagnosis (CAD) are used for detecting brain cancer in the early stages. It does not require ant intervention from humans. It produces reports based on the input MRI images. This has been a major help to radiologist too. This process uses Machine Learning (ML) and Deep Learning. It has shown that it detects the cancer with high accuracy. In this paper, we study different approaches or the Machine Learning techniques for the detection of brain cancer. The techniques/methods of Deep Learning or Machine Learning includes data pre-processing, feature extraction, feature selection, feature augmentation, feature reduction and feature classification. According to a study, Neurosurgeons are more confident in terms of their patient cancer diagnosis from Artificial Intelligence (AI) and can leave their operating room more with confident than ever (SHAH , et al., 2022). And this is a great achievement in the field of Machine Learning and Deep Learning. Here, in this report we study how different CNN models are implemented and how are they able to detect brain cancer with high accuracy.

2. Aim & Objectives

The aim of this project is to study different techniques that can be implemented for the detection of brain cancer. And to study how these Machine Learning algorithms were implemented and were able to detect brain cancer. As discussed, early treatment or early diagnosis of such cancer is always necessary for the treatment of such cancer.

2.1. Aim

- To study and find the learnings about the complex system with respect to deep learning techniques especially the use of different Convolutional Neural Network (CNN) architectures in the field of brain cancer detection.

2.2. Objectives

The main objectives of this project are listed below:

- To research which models performs well in class imbalance problem
- To learn how different algorithms/architectures of CNN are compared and used for the classification, detection, and segmentation of brain cancer.

3. Literature review

The research describes an automated approach for identifying brain tumors using MRI scans. The authors propose a deep convolutional neural network (CNN) with six learnable layers for this task. This model is able to learn from the MRI images more quickly and accurately than traditional deep learning models, even with a smaller amount of training data. The authors suggest that their approach could be useful for a variety of MRI classification tasks, and the results of their experiments show that the model can accurately diagnose and predict brain tumors. The model is also transparent, displaying the predicted image class and the actual image class for each image. (Tiwari, et al., 2022).

In this study, the authors introduced a method for segmenting brain tumors using a convolutional neural network (CNN). They used an encoder-decoder architecture for the CNN and proposed a dense feature sharing strategy within each encoder block. They also shared the characteristics learned at each encoder with the corresponding decoder, which improved the accuracy of the brain tumor segmentation map. The authors tested their proposed network on a dataset of brain

MRI slices, using 70% for training and 30% for testing. They evaluated the performance of their method through both qualitative and quantitative analysis and found that it outperformed other current methods for brain tumor segmentation. (Bhalerao, et al., 2022).

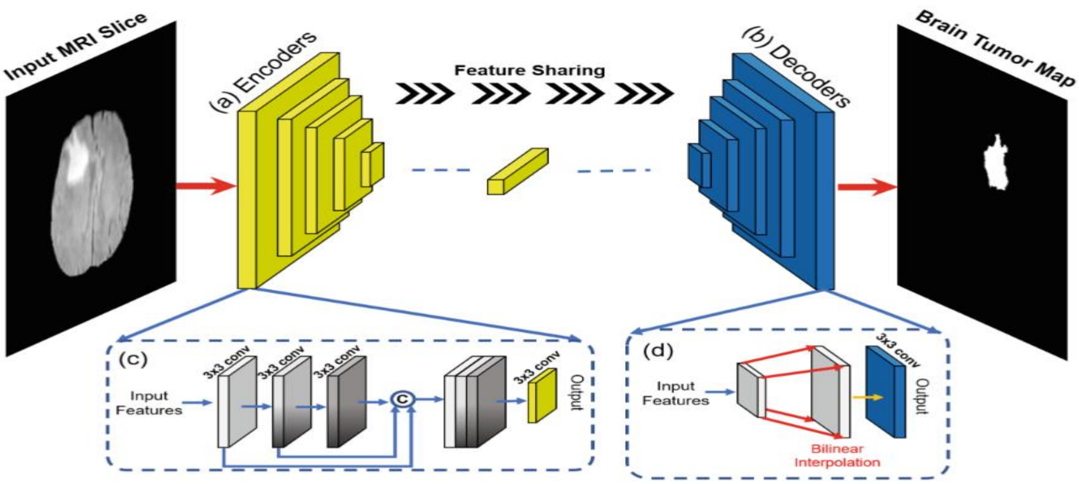

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Figure 1: Brain Tumor Segmentation Approach

In this research paper, the authors use different data mining techniques for the prediction of brain tumor. The authors compared different segmentation algorithms, CNN architectures, SVM, KNN, FVM and GLCM. And it was found that CNN predicted the brain cancer is better than other algorithms as it provided better accuracy and results (Gedam, et al., 2022).

Convolutional neural networks can effectively diagnose brain tumors based on MRI images, as demonstrated in a study that achieved an accuracy of 93% and a loss value of 0.23264. The number of convolution layers in the network can impact the accuracy of the classification, with more layers resulting in improved accuracy but longer training times. Using image augmentation techniques can also enhance the diversity of the existing dataset, leading to better classification results. To further improve classification results, more images can be added to the dataset, and future research could focus on classifying specific types of tumors (Febrianto, et al., 2020).

In this research, a deep convolutional neural network (CNN) called EfficientNet-B0 was modified with additional layers to accurately classify and detect brain tumors in images. The image quality was improved using various filters and the amount of training data was increased using data augmentation techniques.

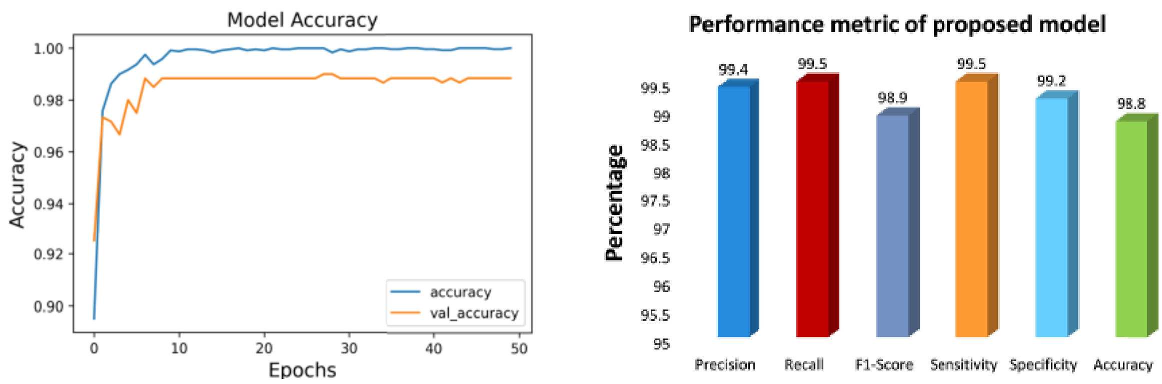

Figure 2: Training and validation accuracy curves & Evaluation metric score of proposed model

The modified EfficientNet-B0 model performed better than other CNN models, achieving high accuracy, precision, recall, and area under curve values in the classification and detection of brain tumors. It had an overall accuracy of 98.87%. The performance of other deep learning algorithms such as VGG16, InceptionV3, Xception, ResNet50, and InceptionResNetV2 was also compared in the analysis (SHAH , et al., 2022).

In this research, the authors developed two deep learning models for detecting abnormalities in the brain and classifying different grades of tumors, including meningioma, glioma, and pituitary tumors. One of the models, the "proposed 23-layer CNN," is designed to handle large amounts of image data, while the other model, the "Fine-tuned CNN with VGG16," is more suitable for smaller datasets. The researchers also used data augmentation to improve the performance of the "Fine-tuned CNN with VGG16" model. When tested on two datasets, both models were effective in predicting the diagnosis of brain tumors, with accuracies of 97.8% and 100% for dataset 1 and dataset 2, respectively. These results outperform those of previous studies and the authors believe that their methods are promising candidates for brain tumor detection. (Khan, et al., 2022).

In this paper, a solution for classifying brain tumors using the state-of-the-art MobilenetV2 140 x 224 architecture was proposed to improve classification accuracy. The experiment showed that the use of MobilenetV2 140 x 224 significantly improved the overall accuracy of predictions, achieving a high accuracy of 94%. The results suggest that transfer learning can be useful for improving the performance of deep learning in classification tasks.

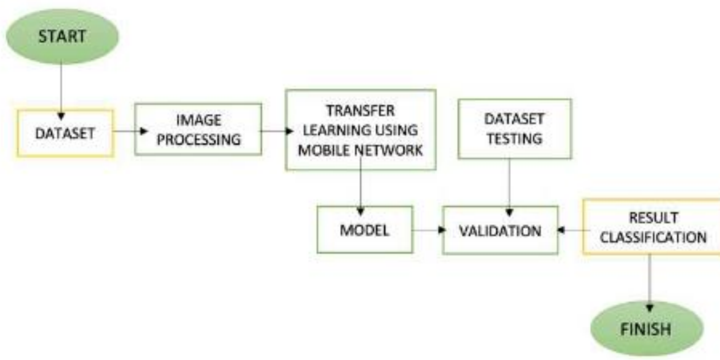

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Figure 3: Methodology using MobileNet

However, there is still room for improvement in the classification of brain tumors, and future work could involve comparing the performance of MobilenetV2 with other state-of-the-art neural network architectures (Arfan, et al., 2021).

The researchers in this study used a CNN called GoogLeNet to classify brain tumors into three categories: glioma, meningioma, and pituitary. The CNN was trained and tested on medical imaging datasets, and the images were pre-processed by normalizing their intensity and resizing them. The CNN was trained using the backpropagation algorithm, and its performance was evaluated using accuracy, specificity, and F1 score. The results of the proposed model were better than those of other models. The use of the Internet of Medical Things and smart devices interconnected through the internet are seen as important in the transformation of the healthcare system through the use of computer-aided diagnosis systems. Early detection and classification of tumors can greatly improve survival rates for patients with life-threatening diseases such as brain tumors, which often lead to cancer. The proposed CNN model could potentially contribute to this effort by accurately classifying brain tumors. (Sekhar, et al., 2022)

4. Analysis and Findings

In the context of computer-aided diagnosis (CAD) of brain tumors, CNNs can analyze medical images, such as MRI or CT scans, to identify and classify different types of tumors.

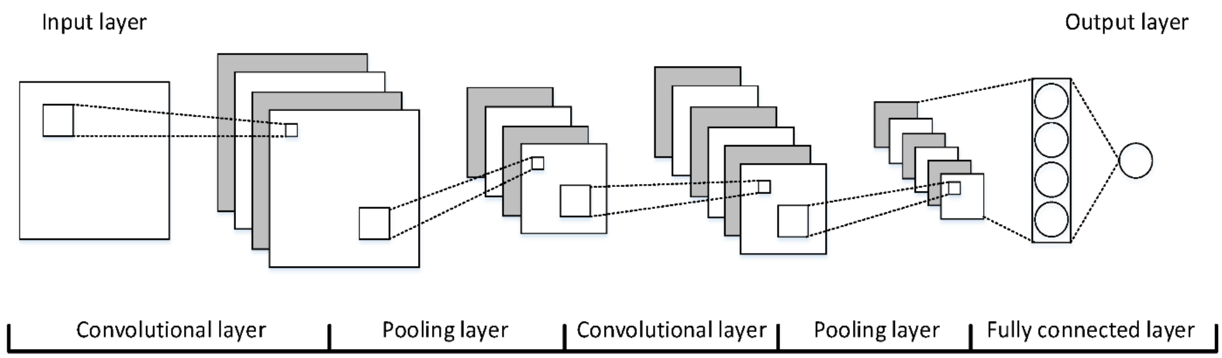

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Figure 4: CNN Model Architecture

A CNN's architecture is made up of several layers, including convolutional layers, pooling layers, and fully connected layers. The pooling layers minimize the dimensionality of the feature maps created by the convolutional layers, while the convolutional layers extract features from the input pictures. These attributes are then used by the fully linked layers to categorize the input pictures. A CNN may be trained to reliably identify and categorize brain tumors in new pictures by utilizing a huge collection of medical images labeled with the right diagnosis. The architecture of the CNN can be designed to optimize the network's performance on the specific task at hand, such as by using more or fewer layers, different types of layers, or different parameters for the layers. This can help to improve the accuracy and efficiency of the CAD system for brain tumors.

The confusion matrix is used to assess a model's performance and display the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) (FN). These values can then be used to compute precision, recall, and specificity, as specified below:

Precision = TP / (TP + FP)

$$Precision = \frac{TP}{TP + FP}$$

Figure 5: Precision Formula

Recall = TP / (TP + FN)

$$Recall = \frac{TP}{TP + FN}$$

Figure 6: Recall Formula

Specificity = TN / (TN + FP)

$$Specificity = \frac{TN}{TN + FP}$$

Figure 7: Specificity Formula

The confusion matrix and these measures are commonly used to evaluate the performance of classification models and can provide insight into the trade-offs between false positives and false negatives. The F1 score is a statistical metric used to assess the accuracy of a model. It is defined as the harmonic mean of accuracy and recall and is determined by merging precision and recall into a single measure. A high F1 score suggests that the model strikes a good balance between properly detecting positive and incorrect situations. It is frequently used to assess the effectiveness of classification models, especially when the class distribution is skewed.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Figure 8: F1-Score Formula

Now, the comparison of the results of several research conducted in our study is shown in the below diagram:

Authors	**Dataset**	**Method**	**Accuracy**
(Tiwari, et al., 2022)	MRI from the Kaggle licensed CCO: Public Domain	CNN	99%
(Bhalerao, et al., 2022)	BraTS-2015 database	Encoder-Decoder based network architecture	96%
(Febrianto, et al., 2020)	MRI Images for Brain Tumor Detection obtained from Kaggle	CNN	93%
(Khan, et al., 2022)	CE-MRI Fig share dataset & Harvard repository dataset	26-layer CNN & Fine-tune with VGG16	97.85% & 100%

(SHAH , et al., 2022)	Subset of the authorized benchmark Brats2015 brain tumor dataset	EfficientNet-B0	98.87%
(Arfan, et al., 2021)	Three different Brain tumourMR images obtained from Kaggle	MobilenetV2	94%

Figure 9: Comparison of different methods implemented

According to several research, researchers are trying to improve the accuracy of convolutional neural networks (CNNs) for brain cancer detection:

- By using larger and more diverse datasets: By training a CNN on a larger and more diverse dataset of medical images, researchers are improving the network's ability to generalize to new cases and reduce the risk of overfitting.
- By tuning network architecture: The architecture of a CNN, including the number and type of layers and the parameters of those layers, can impact the network's performance. Researchers are experimenting with different architectures to find the one that provides the best accuracy for the task at hand.
- By incorporating domain knowledge: Researchers are incorporating their understanding of the medical domain into the design of the CNN, such as by using specialized layers or loss functions that are tailored to the specific characteristics of brain tumors.
- By using transfer learning: By starting with a pre-trained CNN and fine-tuning it on a specific task, researchers are taking advantage of the knowledge learned on a large dataset and improve the accuracy of the network.
- By using data augmentation: By artificially generating additional training examples through techniques such as image rotation, scaling, and cropping, researchers are improving the robustness of the CNN and increasing its accuracy.
- By using ensembles: By combining the predictions of multiple CNNs, researchers are improving the overall accuracy of the system.

Overall, CNNs have shown great promise in the detection and classification of brain tumors and have the potential to significantly improve the diagnosis and treatment of brain cancer.

5. Conclusion

Brain cancer is a serious health concern that affects millions of people around the world. Early detection of brain cancer is crucial for successful treatment, and advances in technology have made it possible to use convolutional neural networks (CNNs) for detection. Different architectures of CNNs can be used for brain cancer/tumor detection, and these architectures can vary in terms of their complexity and the accuracy of their predictions. Researchers are constantly working to develop new and improved CNN architectures that can effectively detect brain cancer, and their efforts are helping to improve the accuracy and speed of brain cancer detection. Ultimately, the use of different architectures of CNNs for brain cancer/tumor detection is a promising area of research that holds great potential for improving patient outcomes.

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