Bachelor of Science in Computer Science and Engineering

Brain Tumor Detection from MRI Using Deep CNN

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November, 2023

CANDIDATES’ DECLARATION

This is to certify that the work presented in this project, titled, “Brain Tumor Detection from MRI Using Deep CNN”, is the outcome of the investigation and research carried out by me under the supervision of Md. Sajjatul Islam.

It is also declared that neither this project nor any part thereof has been submitted anywhere else for the award of any degree, diploma, or other qualifications.

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CERTIFICATION

The project titled “Brain Tumor Detection from MRI Using Deep CNN” " submitted by Khadija Binti Yasin ID No: 18302016, Session:2018 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of Bachelor of Science in Computer Science and Engineering on November 2023

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ACKNOWLEDGEMENT

First, 1 am thankful to the almighty Allah for giving me a chance to complete this thesis. I would like to consider my gratefulness to my honorable supervisor Md. Sajjatul Islam, Assistant Professor, Computer Science and Engineering for the invariable help of my research work. His command helped me to find the solution to my thesis work.

I would like to be grateful to my teachers in the Computer Science and Engineering department for their support during my studies. I am also thanks to my gratitude to all of my friends, senior, and junior who directly or indirectly helped me with the ideas and resources of the research.

Finally, I would like to thank my family, my parents, and my precious ones for supporting me piously all over my life.

Chittagong
November 2023

Khadija Binti Yasin

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ABSTRACT

Brain cancer is considered one of the most aggressive tumors, with a significant impact on patient survival rates. Unfortunately, roughly 72% of people diagnosed with this cancer do not survive. This research proposes a strategy designed to detect and localize brain cancer by presenting an automated methodology for the detection and localization of brain cancer. The method employs magnetic resonance imaging analysis. By exploiting the information provided by brain medical pictures, the suggested method seeks to enhance the identification and exact localization of brain cancer to improve the prognosis and treatment outcomes for patients. We exploit the CNN model to automatically detect and localize brain cancer: in the analysis of MRI brain images we obtain a precision of 0.71 and a recall of 0.72 in brain cancer detection while relating to brain cancer localization, thus showing the effectiveness of the proposed model for brain cancer detection and localization.

Chapter 1

1. Introduction

1.1 Background

The Central Nervous System (CNS), which includes the brain and spinal cord, is responsible for controlling a large number of controls many biological processes and activities [1]. The human brain's exceptional complexity is built on its intricate physical constitution, which includes a large number of neurons, extensive interconnection, specialized regions, and flexibility. Because of its complexity, the brain is capable of performing a wide range of functions, from basic survival processes to high-level cognitive operations, making it one of the most fascinating and perplexing organs in the human body [2]. CNS illnesses such as stroke, infections, brain tumors, and migraines are multifaceted conditions with diverse presentations and challenges in diagnosis, evaluation, and treatment. Advancements in medical imaging, diagnostic tools, and treatment strategies are continually evolving to improve patient outcomes and address these difficulties. Researchers and healthcare professionals are actively working to enhance our understanding of these conditions and develop more effective interventions [3]. Brain tumors are a complex group of diseases with diverse characteristics, making their early diagnosis a significant challenge for healthcare professionals. Advancements in imaging technology and the potential integration of AI hold promise for improving the accuracy and efficiency of brain tumor detection, ultimately leading to better patient outcomes. However, this field of research and clinical practice continues to evolve as experts work towards more effective diagnostic strategies and treatments for brain tumors [4]. Primary brain tumors originate within the brain itself and can be either benign or malignant. They are classified based on their cell of origin and behavior. In contrast, secondary or metastatic brain tumors are the result of cancer cells spreading to the brain from another part of the body. The distinction between primary and secondary brain tumors is essential for determining appropriate treatment strategies and understanding their behavior [5]. Secondary brain tumors are malignant brain tumors that develop as a result of cancer cells spreading from another section of the body. They are almost always malignant and pose a major health risk. Early detection and therapy are critical in treating these tumors and addressing the underlying primary cancer cause [6].

1.2 Motivation of The Research

The prevalence and incidence of primary brain tumors in the United States emphasize the significance of ongoing research, medical improvements, and comprehensive care for people impacted by these diseases. Understanding the complex nature of prognosis and taking factors like age into account is critical for delivering the best care and support to brain tumor patients [7], whereas those aged 65–74 had a 29.3% survival rate. Early detection of primary brain tumors, including meningioma, glioma, and pituitary tumors, is crucial for improving the chances of successful treatment and increasing the likelihood of survival. Each of these tumor types presents unique challenges and treatment approaches, making accurate diagnosis and timely intervention essential in clinical practice [8]. The majority of meningioma cases occur near the meninges tissues on the brain or spinal cord periphery [9]. It's important to note that the prognosis, treatment, and outcomes for these tumors can vary widely based on factors such as tumor type, location, size, and grade. Early diagnosis, accurate characterization, and a multidisciplinary approach to treatment are essential in managing these brain tumors and optimizing the quality of life for affected individuals [10]. These innovative approaches aim to enhance the accuracy and safety of brain tumor diagnosis, reduce patient discomfort, and enable more personalized treatment plans based on a comprehensive understanding of the tumor's biology. They represent promising advancements in the field of neuro-oncology [11]. Histopathological tumor grading (Biopsy) presents its own set of challenges, such as intra-tumor heterogeneity and disparities in the subjective judgments of different experts [12]. These traits complicate and constrain the diagnosis process for malignancies. The importance of a quick and precise diagnosis of brain tumors cannot be overstated. It is the cornerstone of effective treatment planning and has a profound impact on patient outcomes, including survival rates, quality of life, and the ability to make informed care decisions. Healthcare professionals strive to employ the most advanced diagnostic techniques and tools to ensure the best possible outcomes for individuals affected by brain tumors [13]. Today's radiologists must rely on their own skills and subjective interpretation of photos to make detection and choices manually [14].

Accurate diagnosis by human visual examination alone is difficult due to the vast range of practitioners' expertise and the inherent complexity of brain tumor images [15]. MRI scanning is extensively applied in neurology because it enables for an in-depth examination of the skull and brain [16]. It gives axial, coronal, and sagittal imaging for a more thorough review [17]. In addition to creating high-resolution pictures with great contrast, MRI also has the benefit of being a radiation-free technology. For this reason, it is the recommended noninvasive imaging tool for diagnosing several kinds of brain malignancies [18].

1.3 Problem Statement

Artificial intelligence (AI) plays a crucial role in the identification and diagnosis of brain tumors, making it a viable complement to the notoriously challenging field of brain tumor surgery. Subsets of artificial intelligence like machine learning (ML) and deep learning (DL) have transformed neuropathological techniques. Preprocessing of data, feature extraction, feature selection, feature reduction, and classification are only a few of the steps involved in these methods. According to ref. [19], AI has helped raise neuropathologist's assurance in making diagnoses of brain tumors, allowing doctors to make better judgments for their patients. Recent breakthroughs in deep learning have led to a wide range of beneficial applications [20] in domains as divergent as pattern classification, object detection, voice recognition, and decision-making. Researchers in the healthcare industry have used a variety of ML algorithms, such as support vector machines (SVMs), k-nearest neighbor (k-NN), decision trees, Naive Bayes, and DL algorithms, such as trained convolutional neural networks (CNNs), VGGNets [21], GoogleNet [22], and ResNets [23], to aid in the diagnosis of cancer.

In addition, research progress is hampered by the paucity of comprehensive medical datasets due to privacy constraints that prevent the exchange of patient information. In addition, because existing approaches lack precision and recall, they are inefficient and take too long to classify images, which can postpone the commencement of treatment [24]. It can be utilized to diagnose neurological illnesses and analyze images of brain tumor cancer [25].

1.4 Research Objective

The major purpose of my study is to detect and localize brain tumors from an MRI Image at a minimal cost. We also wanted to get a better outcome so that our model would be more applicable. Our thesis goals are creating a detecting system and establishing a low-cost system that is affordable for a developing country like Bangladesh.

1.5 Research Scope

A new automated method based on the state-of-the-art CNN model is fine-tuned using our proposed module, which can replace conventional invasive brain tumor detection and boost overall detection accuracy. The following are the significant findings of this research:

- In order to boost the accuracy of the brain tumor recognition system, a large dataset of brain tumor images was acquired from open-source resources.

- To increase the readability of low-resolution MRI images, a three-stage image preparation approach was put in place. In addition, we evaluated the influence of overfitting on classification accuracy and applied a data augmentation strategy to increase performance on limited datasets.

- We created a completely automated brain tumor detection model utilizing deep learning algorithms and CNN. This model seeks to reduce false detections and ultimately minimize the loss of human lives associated with brain malignancies.

- After evaluating the effects of three different attention methods on the model's output, we opted to employ the CBAM (Convolutional Block Attention Module) module. The decoupled head and CBAM attention mechanism have been verified to be successful in boosting the performance of the brain tumor detection model.

- We merged the SPPF+ (Spatial Pyramid Pooling Fast+) and BiFPN (Bi-directional Feature Pyramid Network) components to handle the difficulties of detecting small-size brain tumors. These modules enable the model to zero in on localized tumors and share the obtained information across several spatial scales. Improved sensitivity to localized brain tumors is a major benefit of the BiFPN feature fusion approach that contributes to the success of the brain tumor detection model.

In the following part, we cover previous research on brain tumors utilizing a variety of machine-learning methods. In Section 3, we present a full summary of this study, including both the suggested architecture and the methodology. In addition, we examine the deep learning models and performance indicators that were applied in this investigation. In Section 4, we go into the outcomes of our examination of the deep learning models' functioning. Section 5 presents a final appraisal of this research and looks ahead at some of the prospects for this field of study.

1.6 Thesis Organization

In the first chapter, a special part on the Detect Tumor and its localization, the backdrop behind the study, the motivation of the research, the problem statement, and the research target are described. The other components connected to our research are as below:

In the next chapter, I will explain, the literature review where we can see some research studies that have already been done on the same topic of traffic concerns, their employed methodology, and Healthcare based on their work comparison among my work and their work. In their chapter, we shall examine the methods of our job. In the technique of my work, I will describe data collection, and pre-processing of data and will analyze our work. The findings of the methodology will be discussed, in chapter four. The last chapter is the ending chapter. Here I will present the conclusion part where there will be the whole summary of my effort. Here I have outlined what work I will undertake in the future for the betterment of the work.

Chapter 2

2. Literature Review

2.1 Introduction

In a literature review, a researcher reviews the prior work, research, conference papers, books, articles, etc. With it, one can find out what work has previously been done on the issue, summarize the full topic, and find out what lacking in the work. After assessing they can work on constraints and overcome the limitations to acquire better results.

2.2 Previous Literature

An extensive analysis of the various techniques for interpreting brain MRI data was carried out by Francesco et al. [26], who also compared and contrasted the benefits and drawbacks of deep learning and conventional machine learning techniques. Stochastic gradient descent (SGD), average precision (AP), precision–recall curve, precision, recall, and YOLO v8s were the methodologies used. obtained a 0.943 precision and 0.923 recall using their methods, indicating a difficulty in fine-tuning the YOLO v8 model (precision 0.935, recall 0.388). To close performance disparities in the YOLO v8 model—particularly in recall—further research and optimization are necessary. This highlights the importance of striking a balance between deep learning and conventional machine learning techniques for diagnosing brain MRIs.

Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Multilayer Perceptron (MLP), Logistic Regression, Naïve Bayes, and Random Forest were the methodologies employed by Tonmoy Hossain et al. [27]. SVM yielded 92.42% accuracy in the results, while CNN produced 97.87% accuracy. More effective brain tumor segmentation will be achieved in the future with 3D brain scans. Future research prospects include addressing the difficulty of assuring robustness in deep learning models and enhancing methods like SVM for improved accuracy. Specific goals will be to improve the overall efficiency of cancer detection systems and refine 3D brain tumor segmentation.

Francesco et al. [28] achieved an accuracy range of 97.83% to 99.67% in the identification of brain cancer using the VGG16, ResNet50, Alex_Net, and MobileNet models. Determining the cancer grade raises the bar for accomplishments. The problem is to provide resilience across varied datasets and handle any biases in the model, even with high accuracy. This highlights the necessity for generalizability in real-world applications of the established models.

The authors of this work [29] provided numerous methods for using MR images to identify cancers in the brain. The use of 3D CNNs, SVMs, and multi-class SVMs for improving segmentation was examined by the researchers. Excellent performance was demonstrated by several medical image processing applications, including CNNs, deep learning approaches, and the diagnosis of brain tumors. Deep learning techniques produced better classification and segmentation results for brain tumors than conventional machine learning classifiers. To consistently outperform conventional machine learning techniques, the goal is to further optimize and fine-tune the integration of deep learning algorithms, like CNNs, for improved brain tumor classification and segmentation.

A different study [30] developed a deep-learning neural model to extract features from magnetic resonance imaging. These features were then fed into machine learning classifiers such as multilayer perceptron, support vector machines, and naive Bayes. When applying SVMs With an astounding 99.5% classification accuracy, the suggested method highlights the possibility of incorporating deep learning features into conventional classifiers for improved performance. The task at hand is to investigate the suggested technique's generalizability over a wider range of datasets and clinical scenarios, guaranteeing its resilience and dependability in practical applications that extend beyond the particular circumstances of the study.

In a work published in [31], Muhammad Antique Khan et al. analyzed a variety of deep learning and machine learning methods, such as random forest algorithms and support vector machines, for the identification of brain tumors. Interestingly, at 95.14%, the traditional SVMs had the best classification accuracy. Ensuring a balance between traditional and modern methodologies for robust and accurate brain tumor detection is the problem when it comes to further developing and refining deep learning models to surpass or match the high accuracy attained by conventional SVMs for brain tumor identification in MRIs.

In a study, Akmalbek et al. [32] analyzed several deep learning methods, such as CNN and YOLOv7, for the identification of brain tumors. Interestingly, at 99.5%, the traditional SVMs had the highest classification accuracy. The task is to comprehend and tackle the elements that lead to the effectiveness of traditional support vector machines (SVMs), to improve the capabilities of deep learning methods such as CNN and YOLOv7 for brain tumor detection.

In a study by Mohamed Amine et al. [33], numerous machine-learning and deep-learning methods for diagnosing brain tumors were analyzed. These methods included the CNN algorithm and CNN networks, which achieved 95% recall, 95.44% accuracy, and 95.36% of F1-score. Despite the strong performance, the study's difficulty is figuring out how to make the CNN-based approach even more resilient and improved so that it may be applied to a variety of datasets and clinical scenarios with more consistent and generalizable results.

The accuracy of this optimized system was tested at 98.9% by Praveen Kumar Ramtekkar et al. [34] using the Convolutional Neural Network (CNN), Accuracy, Precision, and Recall parameters. Notwithstanding the elevated precision, the obstacle resides in comprehending and resolving plausible constraints, guaranteeing the resilience and applicability of the Convolutional Neural Network in practical situations for all-encompassing diagnostic uses.

Convolutional Neural Network (CNN) algorithms are among the machine-learning and deep-learning methods that Soheila Saeedi et al. [35] analyzed in their study for the diagnosis of brain tumors. Notably, for the identification of brain tumors in MRI images, the traditional SVMs obtained the highest classification accuracy, at 95%. The auto-encoder network is more complicated than this suggested network. The task is to improve deep learning methods even more, especially auto-encoder networks, such that they can either equal or surpass traditional SVM classification accuracy in the identification of brain tumors from MRI scans.

2.3 Conclusion

There are various types of algorithms utilized. To have a satisfactory outcome, they employed feature extractions, augmentation, annotation, and many more techniques. Forget improved accuracy performance. In our effort, we also tried to locate and localize Tumor and work on MRI image analysis.

Chapter 3

3. Research Methodology

To build an effective deep learning model for the detection and localization of brain cancer from MRI scans, it is essential to have a dataset that consists of brain cancer MRIs along with corresponding annotations (i.e., bounding boxes) indicating the localization of the cancerous regions.

We underline the relevance of having a high-quality dataset that includes both the MRIs and exact annotations of the tumor localization. Such a dataset serves as the foundation for training the object detection model efficiently. By having accurate annotations, the model may learn to detect and find the exact locations within the brain MRI scans that indicate the presence of cancer.

Having a trustworthy and well-annotated dataset is vital in the construction of a robust and accurate object identification model for brain cancer detection and localization. It ensures that the model is trained on representative and useful data, enabling it to make precise predictions when applied to new, unseen MRI scans. The following approach is used in the study, which has five (5) stages as shown in Figure 3.1 and named Data Collection, Data preprocessing, Model Training, Modeling, and Testing the Trained Model.

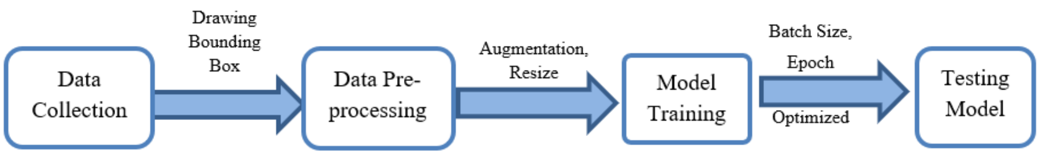

Figure 0.1 Methodology Stages

3.1 Data Collection

Every project needs data, and every experiment depends on the data. Important information that Brain MRI scan images can be utilized to construct models for identifying tumors in a range of applications. A recent study has focused on classification challenges to identify the tumor and not tumor well-known datasets that aid in finding the tumor. Various datasets may be utilized to examine brain tumor identification, however, there aren't many faces of Indian heritage that are suited for a teaching context. This effort focuses on detecting and localizing tumors utilizing the dataset accessible to people of Bangladesh pupils. There is already an available dataset on the internet on which numerous works have been conducted. Some datasets have been acquired through Kaggle [36]. There are many other dataset resources available on the internet which are from various countries. However, there exist certain MRI scan datasets.

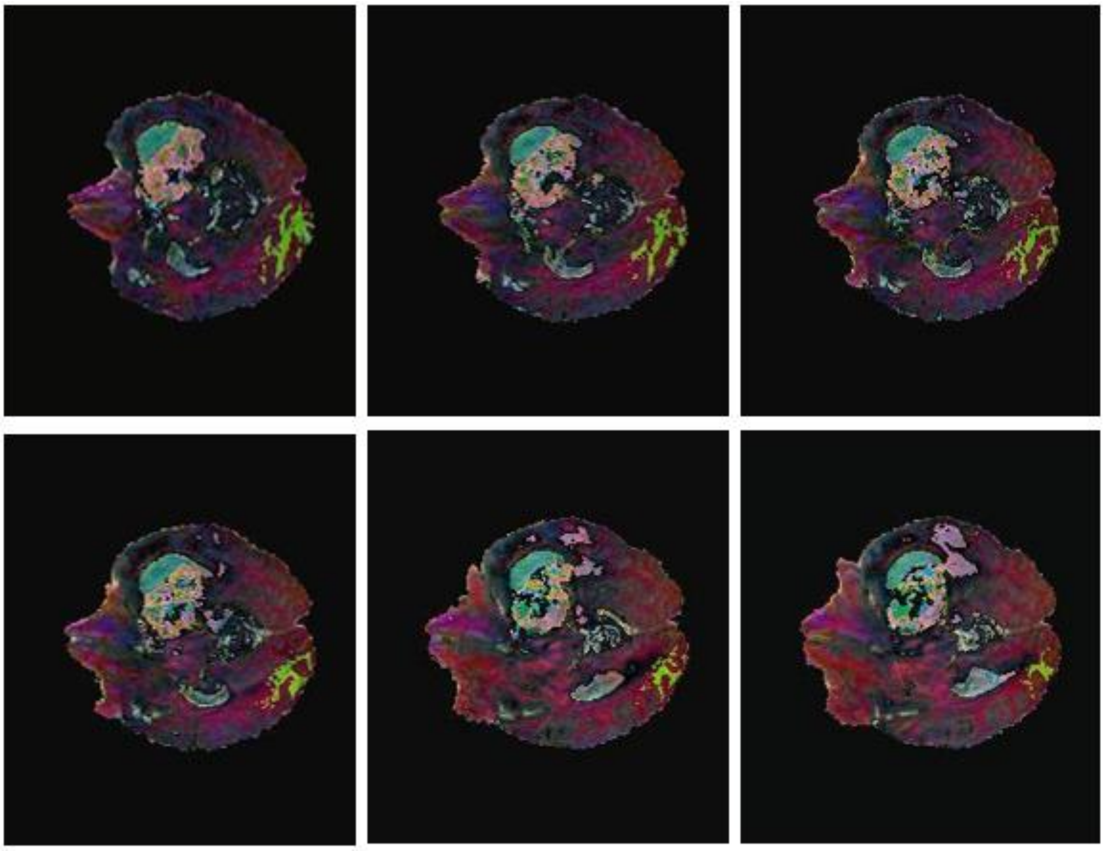

Figure 0.2 A sample of MRI images from the brain tumor dataset

Within the MRI displayed in Figure 3.2, it is possible to detect an RGB, virtually with the area on the Bottom side of the image, showing where the brain tumor is located.

Table 0.1 A table containing some of the data from the Dataset

Filename	Width	Height	Class	Xmin	Ymin	Xmax	Ymax
001.jpg	240	240	Primary	106	55	133	77
002.jpg	240	240	2nd Stage	112	66	168	89
003.jpg	240	240	2nd Stage	105	53	139	82
004.jpg	240	240	Primary	92	66	169	89
005.jpg	240	240	Primary	99	67	146	86

3.1.1 Summary of the dataset

A tabular structure with the following columns is included in the dataset: filename, width, height, class, xmin, ymin, xmax, and ymax.

The annotations for objects in certain photos are represented by each row.

The resolution of images is always 240 x 240 pixels (columns for width and height).

Classes, such as "Primary" and "2nd Stage," are assigned to the objects in the photos and are listed in the class column.

The bounding box coordinates (xmin, ymin, xmax, ymax) represent the annotated items' spatial location and extent. Annotations for objects in photos, such as filenames, class labels, and bounding box coordinates, are displayed in the first few rows.

To learn more about the named objects, more investigation could entail displaying these bounding boxes on related pictures.

Before using the data for machine learning tasks, preprocessing processes like managing missing values or encoding categorical variables could be required.

The distribution and features of the labeled objects can be used to inform future research and model development. This dataset appears appropriate for problems involving object detection or localization in images.

3.2 Data Preprocessing

I have collected data from the Kaggle dataset[36]. That dataset has around 9058 images of brain MRI Scan Images. The collection consists of 9058 annotation files. These files state the exact position of the items with labels in the accompanying image. The annotated values are recorded in XML files. The data files are divided into 2 directories. The processed data enhanced the accuracy of the model. After acquiring road photos, I divided the data into train and validation sets. In the training dataset, there is 80% data and in the validation set, there is 20% data. In the dataset, there is a complete dataset wherein the train contains 5832 data and, in validation, there is 1460 data. So, there is a total of 7292 data in the dataset.

3.2.1 Annotated Images

In order to create a model that is both efficient and capable of reliably predicting unseen images, a diversified dataset was assembled. This collection features photos acquired from various angles, under varied situations, and displaying different types of tumors. Each image inside the dataset has a unique size. However, to assist further analysis, a preprocessing step is required to resize all the photos to a consistent dimension. Once the pictures are received, we need to define the class for the detection of the bounding box for the brain MRI: in this example, we have one class that is tumor, related to the brain cancer presence. Annotated each image by painting bounding boxes around each recognized object [36].This annotation procedure was conducted utilizing the Label Box web application , a platform developed to execute data annotation tasks.

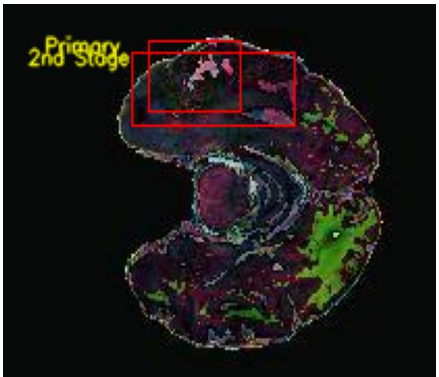

Figure 0.3 Labeling Brain Tumor

3.2.2 Image Augmentation

The third phase involves image augmentation, which refers to a collection of strategies that increase the existing dataset without the requirement for acquiring new examples.

Data augmentation includes applying controlled random adjustments to existing images and generating modified versions of them. This strategy is often applied in training artificial neural networks, as it enables them to “learn” more effectively and accurately as the quantity of the training dataset expands.

Specifically, we apply data augmentation techniques to generate changed images of brain MRIs with controlled random variations, such as rotations, flips, cuts, and trims.

The purpose of implementing data augmentation in this scenario is to make the model capable of effectively detecting cancers regardless of their position within the image. Additionally, enhanced data are applied to solve the issue of overfitting, which arises when a statistical model becomes overly specialized in fitting the observed data sample due to an excessive number of parameters compared to the number of observations.

By providing changes through data augmentation, the structured neural network can learn to recognize repeating patterns from the augmented data, rather than simply memorizing individual samples. This helps the model create more generic rules and minimizes the likelihood of misclassifying unseen patterns. Data augmentation plays a crucial role in boosting the model’s capacity to generalize and perform effectively on unseen images.

After receiving the upgraded brain MRIs, together with the associated information regarding cancer localization (i.e., the class) and bounding boxes, the next step is to develop a deep learning model—and annotation duties.

3.3 Machine Learning

Machine learning is an area of artificial intelligence (AI) that focuses on building algorithms and models that enable computer systems to learn and make predictions or judgments without being explicitly programmed. The underlying idea behind machine learning is to allow computers to discover patterns and make sense of data via experience and learning, much to the way humans learn from their experiences.

3.4 Deep Learning

Deep Learning (DL) is a subset of Machine Learning (ML) that deals with algorithms inspired by brain structure and function known as artificial neural networks. Without explicit programming, ML-based systems can learn and enhance their knowledge through experience. The quality of differentiating characteristics between the provided classes is one of the essential factors that determine the ML model's performance. Manual extraction of such traits, on the other hand, is a laborious and sometimes complex operation. Self-feature extraction models, which fall under the ambit of DL approaches, can address this problem. A hierarchical network with several neural network layers is used in the DL architecture. Many disciplines of research have been inspired by the DL framework, including human action recognition [37] and stock trading [38]. The CNN is constructed on a DL structure.

3.4.1 Convolution Neural Network

The CNN is a form of feed-forward multi-layer neural network that uses the back-propagation approach to collect features and optimize model weight [39]. CNN-based architectures have lately emerged as one of the most popular Deep Learning networks for a wide range of visual computer applications, including facial emotion identification and object detection [40]. CNN has three fundamental properties: perception of areas, weight distribution, and downsampling. These attributes eliminate low-level feature extraction overhead and allow the model to acquire high-level features that are translation, rotation, and distortion invariant. Figure 3.4 illustrates a sample CNN model made up of three blocks. The first is the input block, which is made up of an input layer. The feature extraction block, which consists of convolution and pooling layers, is the second. The third component is a classification block, which is made up of numerous tightly connected layers followed by an output layer.

The input layer of CNN reads 2-dimensional (2D) image pixel data and sends it on to the next feature extraction block. A convolution layer (Conv2D) plus a pooling layer composes the feature extraction block. The Conv2D layer extracts picture feature maps automatically. The pooling layer is in charge of downsampling the feature maps. The Conv2D layer is made up of numerous independent kernels with randomly assigned learnable weights and biases. The weights are numerical values that represent the strength of the connection between the inputs of neurons. During the convolution process, each of these kernels travels through the entire image in both horizontal and vertical directions in line with the stride count, executing a dot product operation known as a convolution operation in the receptive feature maps. The receptive field is the area where the picture data and the kernel overlap. The Convolution operator can be expressed as Equation 3.1

$$\mathrm{y}[\mathrm{m}, \mathrm{n}] = x[m, n] * h[m, n] = \sum_{j=-\infty}^{\infty} \sum_{i=-\infty}^{\infty} x[i, j].\, h[m-i, n-j] \qquad [3.1]$$

Where l is the input image, k is the kernel of size d, and b is the bias term y n is the convolution value in the output feature map at point (men), and k is the kernel of size d. The dimension of the feature map is governed by characteristics such as picture padding, kernel size, and stride count. Padding (p) is the number of pixels that are added around an image when it is processed by the CNN kernel. The kernel size (k) of a 2D kernel is its height and width. The stride(s) represented the number of locations that the kernel would traverse over the image. Equation 3.2 determines the size of an output feature map (o), where n is the size of an image. The following layer, the pooling layer, receives a stack of such independent feature maps.

$$O = \left(\frac{n-k+2p}{s} + 1\right) \qquad [3.2]$$

The pooling layer works independently on each feature map to build a set of down-sampled feature maps by extracting dominating scores. Because of the pooled feature maps, the model is insensitive to rotation, translation, and distortion. Pooling procedures are performed in a variety of ways, including max-pooling, min-pooling, and avg-pooling, which are selected depending on the application. The max, min, and average-pooling methods yield the maximum, minimum, and average values from the picture region overlapped by the pooling filter. In the feature extraction block, the pair of convolution and pooling operations is considered one cycle. Many such cycles are normally undertaken for the CNN model to provide the most abstract and independent feature maps. All of these 2D abstracted feature maps are transformed into a single-dimension feature vector by a flattened layer because the feature extraction obstructs the final output. The output of the flattened layer is passed into the classification block's next layer, the dense layer. The convolution and max-pooling operators are represented schematically in Figure 3.5.

Neurons, weights, biases, and activation functions are all part of the dense layer. This layer is in charge of interpreting the extracted feature. An activation function functions as a switch, determining whether or not to activate a neuron by calculating a weighted sum of input values and weights. The activation seeks to introduce non-linearity into the output of a neuron. Popular activation functions include ReLU and using the back-propagation process, these densely connected layers update their randomly initialized weights and biases.

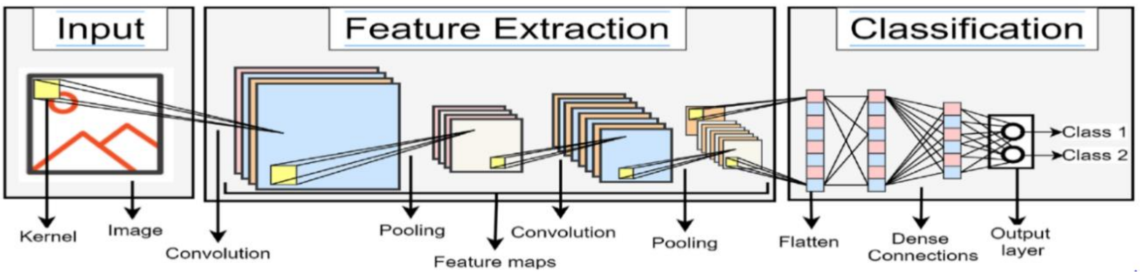

Figure 0.4 A sample CNN block diagram

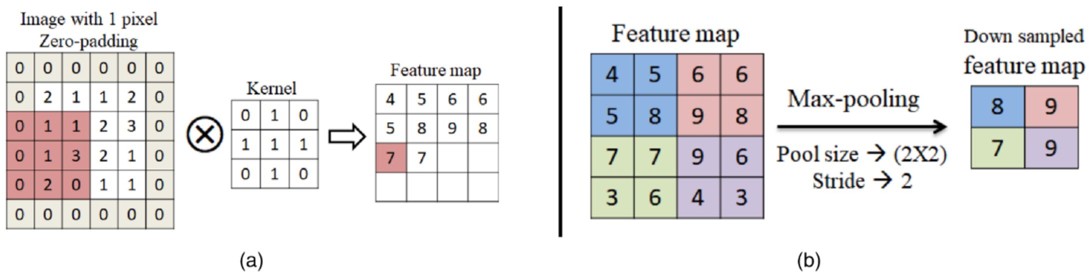

Figure 0.5 Schematic illustration of convolution operator

Finally, the output layer is joined to the densely connected layer. To produce the final results, the output layer has an activation function, either sigmoid or softmax. Softmax is utilized for multi-class classification problems, whereas sigmoid is used for binary-class classification assignments. These functions normalize the output values to a range of 0-1, allowing them to be represented as class probabilities. As a result of the given input, the class with the highest probability will be allocated. In this approach, CNN categorizes the provided image into one class [41].

When training a CNN-based model, some of the primary issues are overfitting, inflating gradients, disappearing gradients, and dataset class imbalance. These concerns have the potential to decrease the model's performance. These issues can be overcome by fine-tuning the model's hyperparameters and utilizing regularization approaches. The hyper-parameters are the parameters that control the model's learning process, such as batch size, kernel size, loss function, and optimizer. Regularization is a predefined strategy for avoiding the model's overfitting problem. L1 and L2 regularization, dropout, data augmentation, and early stopping are examples of these strategies. These concerns were addressed while training the model, resulting in pretty decent classification accuracy.

3.4.2 VGG-16 Model

In our trials, we first used the pre-trained VGG-16 convolutional neural network model, which was modified by freezing some of the layers to avoid data overfitting in the case of our image set, which was quite tiny. Karen Simonyan and Andrew Zisserman [42] proposed the VGG-16 model of 16 convolutional layers in 2014. Regarding the network's input picture, it has dimensions (224 224 3) and comprises 16 layers of convolutional as well as a fixed size filter in (3 3) and 5 layers of Max grouping of size (2 2) on the total network. In contrast, the two layers at the top are entirely coupled by a softmax output layer. The VGG-16 model regards itself as a huge network with over 138 million parameters. It builds deep neural networks by stacking several convolutional layers, which improves the ability to learn hidden characteristics. The VGG-16 network's design is depicted in Figure 3.6.

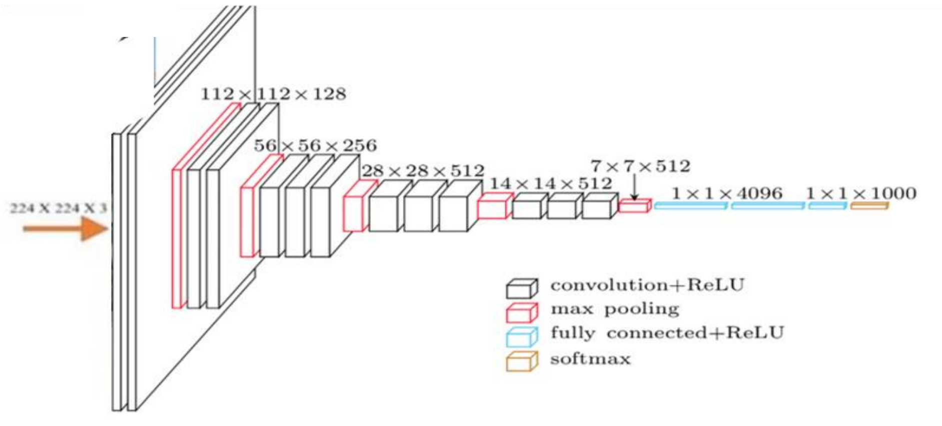

Figure 0.6 VGG-16 model architecture

3.4.3 ResNet50 Model

ResNet50 is a residual network with 50 layers and 26 million parameters. Microsoft did, in fact, introduce a deep convolution neural network model in 2015 [43]. Instead of learning features, the residual network learns residuals, which are the subtraction of learned features from layer inputs. ResNet connects the nth layer's input straight to a (n+x)th layer, allowing more layers to be stacked and a deep network to be built. In our experiment, we refined a pre-trained ResNet50 model. ResNet50's architecture is depicted in Figure 3.7.

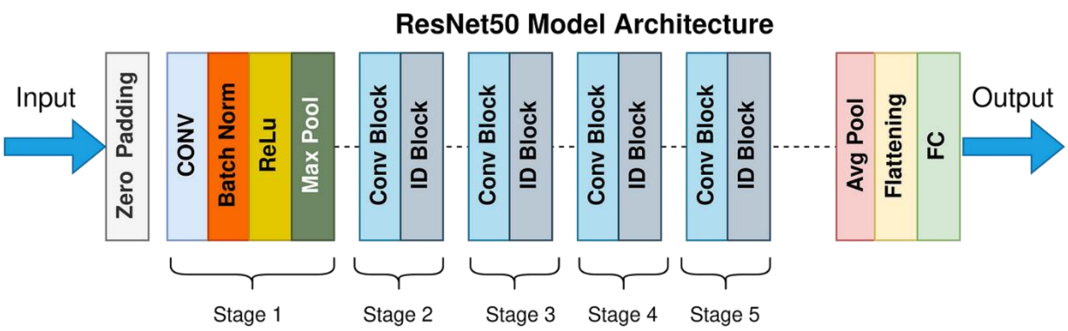

Figure 3.0.7 ResNet50 model architecture

3.5 Base Methodology

Based on the task complexity, computational efficiency, and a moderate dataset size, Convolutional Neural Network (CNN) has been picked as the base model. Difficulties fitting ResNet50 and VGG16, on the other hand, may necessitate a re-evaluation. As this task demands greater accuracy, has intricate features, or benefits from transfer learning, one should consider using VGG16 or ResNet50. Also, ensuring that the hardware resources correspond to the larger models and evaluate the architecture's suitability for the best results. Fitting issues with VGG16 and ResNet50 can be remedied by fine-tuning hyperparameters and studying transfer learning methodologies to ensure alignment with the specific requirements of the MRI image dataset.

Chapter 4

4. Experiment and Result

4.1 Introduction

The concepts and methods for detecting and tumor localization are discussed. Following the data collecting and preprocessing stages, I described the models that I utilized for the detection technique. There, I will describe the outcomes of the model that I constructed.

4.2 Experimental Setup

A computer system with a 10th Generation Intel Core i5-8300H Processor operating at 2.30GHz, 32 Gigabytes of RAM, and an 8 GB NVIDIA GeForce GTX 2050Ti graphics card is used for the implementation and experimentation. Videos from the classroom were collected using a 2MP (People Link Elite FHD-1080 20x optical zoom) IP camera that was put in the department's smart classroom.

4.3 CNN Model Training and Evaluation

4.3.1 Model Training

The proposed CNN architecture, which The suggested CNN architecture, which health care offered brain MRI scan image, was trained using the MRI dataset. Training data represented 75% of the overall dataset, and testing data made up 25% of the total dataset. During model training, the test data was used to fine-tune the model's hyper-parameters. The model is not trained using the samples from the testing data, though. To construct an effective model, we did a lot of trials with various hyperparameter values. Network factors including the activation function, kernel size, optimizer, loss function, batch size, and others are included in these hyperparameters. The submitted face expression image, was trained using the MRI dataset. Training data represented 75% of the overall dataset, and testing data made up 25% of the total dataset. During model training, the test data was used to fine-tune the model's hyper-parameters. The model is not trained using the samples from the testing data, though. To construct an effective model, we did a lot of trials with various hyperparameter values. Network factors including the activation function, kernel size, optimizer, loss function, batch size, and others are included in these hyperparameters.

Table 4.1 offers an overview of the corresponding ideal hyper parameter values that were established after several tests. On different training sets of non-enhanced and augmented training data, the proposed CNN architecture was trained. Figures 4.1 (a) and (b) show, respectively, the corresponding accuracy and loss graphs of these two trained models. Because of the over-fitting issue, Figures illustrate that the model trained on no enhanced training data achieved poorer accuracy and higher loss on test data as compared to the training data. Table 4.2 summarizes the results of the models' training.

4.2.2 Evaluation Metrics

I constructed a confusion matrix to analyze the results. It requires the true positive, true negative, false positive, and false negative values for evaluation. True-positive signifies that the actual number was appropriately predicted. True-negative is rejected correctly. False-positive means that the value is projected to be positive when it is not. False-negative is rejected incorrectly.

Accuracy : The model's accuracy determines how well a machine can predict the results. It is significant when all classes are equally important. All classes are equally important in my line of work. As a result, accuracy is also important in determining the model's accuracy.

$$Accuracy = \frac{\text{TrueNegative}+\text{TruePositive}}{\text{TruePositive}+\text{Falsepositive}+\text{TrueNegative}+\text{FalseNegative}} \quad [4.1]$$

Precision: It is a term used in machine learning to determine the performance of a model. Precision is calculated by dividing the true positive value by the total number of positives.

$$Precision = \frac{TruePositive}{TruePositive+FalsePositive} \quad [4.2]$$

Recall: A recall is an evaluation of a clearly defined true positive. The recall is calculated by dividing the true positive value by the total number of currently available related values.

$$Recall = \frac{TruePositive}{TruePositive+FalseNegative} \quad [4.3]$$

F1 –Score: The F1-score considers both precision and recall, which means it accounts for both FPs and FNs. The higher the precision and recall, the higher the F1 score. F1 scores range from 0 to 1. The closer it is to one, the better the model.

$$F1\ Score = \frac{Precision+Recall}{Recall+Precision} \quad [4.4]$$

Confusion Matrix: We need four attributes to make a Confusion Matrix:

a. True Positives (TP): The model correctly predicted a label and matched the ground truth.
b. True Negatives (TN): The model does not predict the label and therefore is not part of the ground truth.
c. False Positives (FP): The model predicted a label that did not exist in the real world (Type I Error).
d. False Negatives (FN): Although the model does not predict a label, it is included in the ground truth. (Error of Type II)

4.2.3 Model Evaluation

The overall performance of the trained model is covered in this section. Accuracy, precision, recall, and F1-score evaluation metrics as well as a confusion matrix were used to evaluate the training data. The confusion matrix is a table that displays the performance of the mod's true positive (TP), false positive (FP), false negative (FN), and true negative (TN) terms, which are required to calculate the o metrics. Accuracy is the measure of accurate predictions a model makes. A classifier's ability to be precise is not a given.

Table 0.1 List of Hyper-parameters

Hyper-parameter	**Values**
Batch size	64
Activation function	Rectified Linear Unit(ReLU)
Optimizer	Stochastic gradient descent with a learning rate of 1e-4 and momentum of 0.9
Loss function	Categorical_crossentropy
Range of kernels	64→128→256→512→512
Kernel size	3*3
Kernel weight initializer	Cnn_weights_py_dim_ordering_py_kernels_notop.h5
Kernel_Regularizer	L2
Padding	same
Stride	2,2
Pool size	2,2
Normalization	Batch Normalization
Probability of dropout	0.1
Maximum epochs	250
Early stopping	150

4.3 Result and Discussion

The decision between these models is determined by the task at hand, the available resources, and the size of the dataset. ResNet50 is frequently used for very deep structures and workloads requiring great accuracy. For simpler jobs or settings with limited processing resources, VGG16 may be a good alternative. Each model involves trade-offs, and testing is frequently required to discover the best fit for a certain use case. Following the application of the CNN models on our dataset. We have acquired metrics such as validation and testing accuracy, precision, and recall were utilized to assess the model's performance. Precision-measured a positive prediction that was defined as inattentive in our model. The following formula was used to calculate recall.

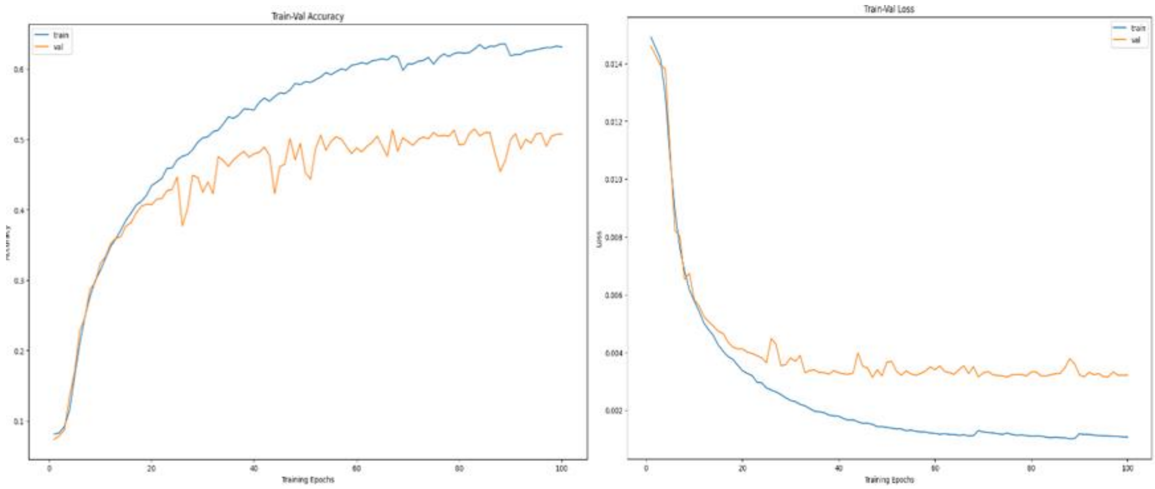

Figure 0.1 Learning curve for the CNN model training and test loss graph

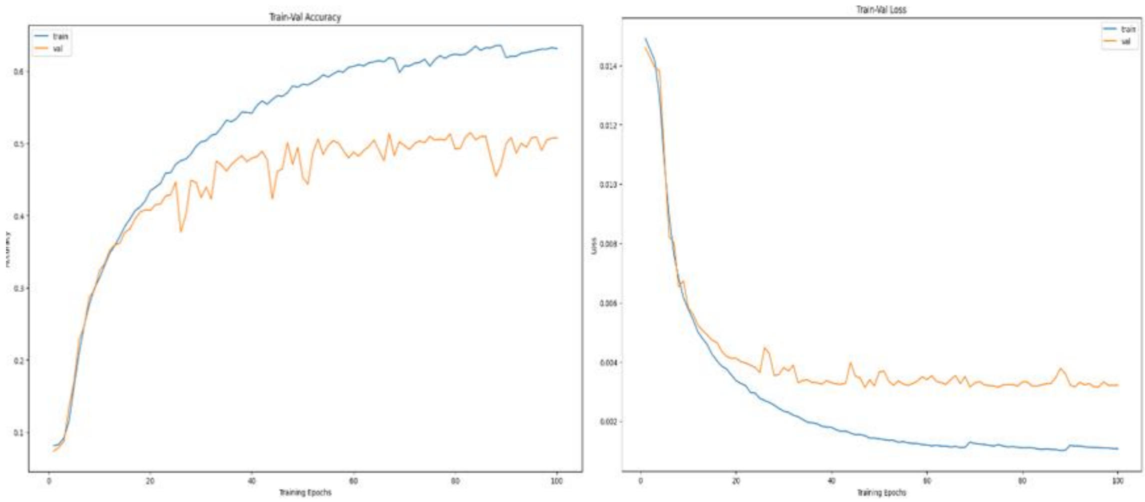

Figure 0.3 Learning curve for the VGG16 model training and test loss graph

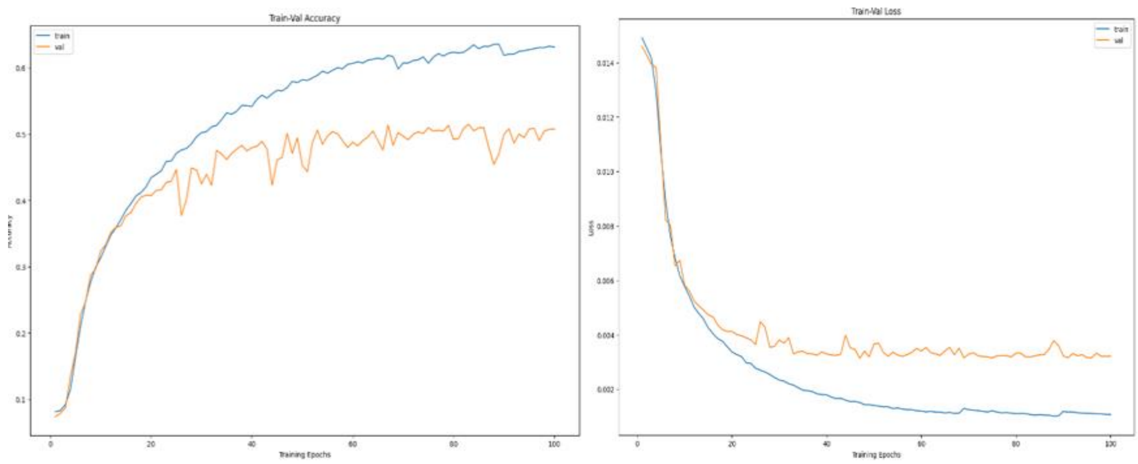

Figure 0.2 Learning curve for the RestNet50 model training and test loss graph

Table 0.2 Evaluation report of the model

Algorithm	Accuracy(%)	Precision(%)	Recall(%)	F1 Score(%)
CNN	72	75	72	73
VGG16	60	55	48	50
RestNet 50	81	82	84	83

4.4. Detection Example

With the purpose of highlighting how the proposed method can be applied in the actual world, in Figure 4.4 we respectively display a set of brain images with the tumor label (with the bounding box added by radiologists) and the same images with the cancerous area detected by the suggested model.

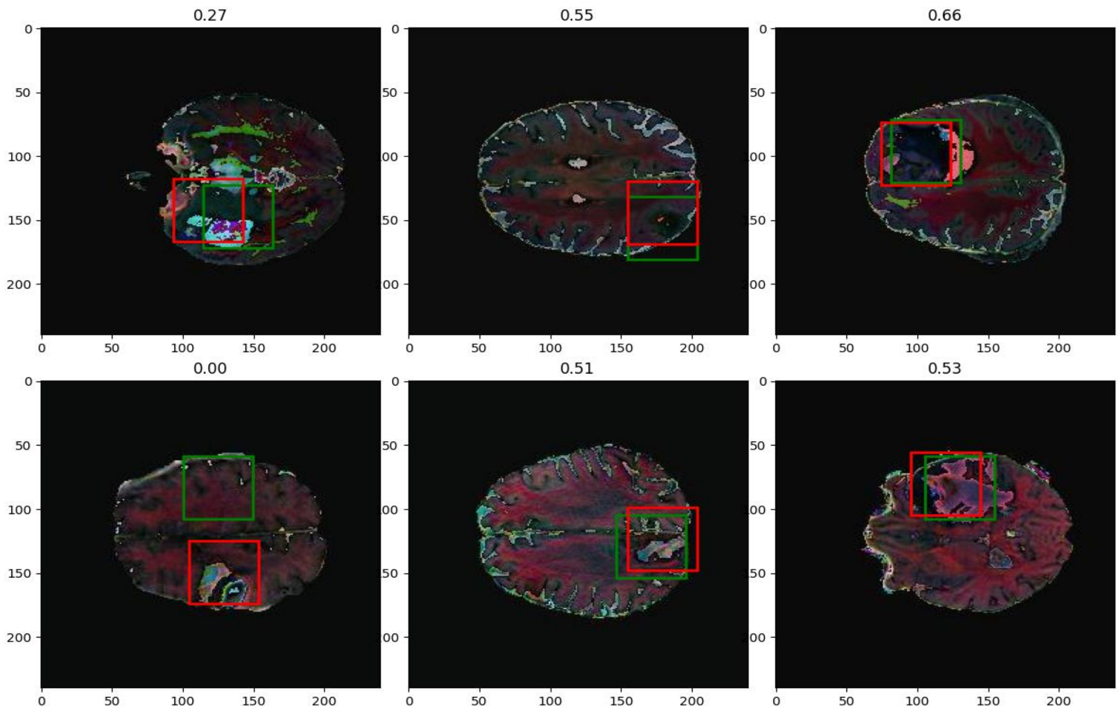

Figure 0.4 Tumor Detection Result (Green Box)

In particular, in Figure 4.4, for each brain image, there is the detail about the bounding box (highlighted in red) related to the localization. We investigate both brain pictures associated with disease and those portraying healthy persons. In the case of healthy brain images, the proposed approach does not add the red boundary box.

Chapter 5

5. Conclusion and Future Work

In this study, we developed a strategy for detecting and localizing the presence of cancer in brain MRIs. The proposed strategy intends to contribute to rapid diagnosis and the prompt beginning of therapy, emphasizing the relevance of early intervention in improving patient outcomes. We use the CNN object detection: in the experimental analysis performed on brain MRIs, we achieved a precision of 0.943 and a recall of 0.923 in the detection of brain cancer. Furthermore, in terms of brain cancer localization, these results illustrate the efficiency of the proposed approach for both the detection and localization of brain cancer.

In future work, we propose to explore the cancer grade detection [44] and to use other object detection models to evaluate the acquired performances, for instance, as the R-CNN, the Fast R-CNN, and the Fast R-CNN. Moreover, considering that medical images are typically composed of slices and not of single images, we will consider extending the proposed approach with whole 3D images;, in the state of the art, there is an implementation of a 3D YOLO model [43] currently exploited for generic object detection.

REFERENCES

1. Lee, Da Yong. “Roles of mTOR Signaling in Brain Development.” *Experimental neurobiology* vol. 24,3 (2015): 177-85. doi:10.5607/en.2015.24.3.177

2. Zahoor, M.M.; Qureshi, S.A.; Bibi, S.; Khan, S.H.; Khan, A.; Ghafoor, U.; Bhutta, M.R. A New Deep Hybrid Boosted and Ensemble Learning-Based Brain Tumor Analysis Using MRI. Sensors 2022, 22, 2726.

3. Arabahmadi, M.; Farahbakhsh, R.; Rezazadeh, J. Deep Learning for Smart Healthcare—A Survey on Brain Tumor Detection from Medical Imaging. Sensors 2022, 22, 1960.

4. Gore, D.V.; Deshpande, V. Comparative study of various techniques using deep Learning for brain tumor detection. In Proceedings of the 2020 IEEE International Conference for Emerging Technology (INCET), Belgaum, India, 5–7 June 2020; pp. 1–4.

5. Sapra, P.; Singh, R.; Khurana, S. Brain tumor detection using neural network. Int. J. Sci. Mod. Eng. 2013, 1, 2319–6386.

6. Soomro, T.A.; Zheng, L.; Afifi, A.J.; Ali, A.; Soomro, S.; Yin, M.; Gao, J. Image Segmentation for MR Brain Tumor Detection Using Machine Learning: A Review. IEEE Rev. Biomed. Eng. 2022, 16, 70–90.

7. Yavuz, B.B.; Kanyilmaz, G.; Aktan, M. Factors affecting survival in glioblastoma patients below and above 65 years of age: A retrospective observational study. Indian J. Cancer 2021, 58, 210.

8. Fahmideh, M.A.; Scheurer, M.E. Pediatric brain tumors: Descriptive epidemiology, risk factors, and future directions. Cancer Epidemiol. Prev. Biomark. 2021, 30, 813–821.

9. Nodirov, J.; Abdusalomov, A.B.; Whangbo, T.K. Attention 3D U-Net with Multiple Skip Connections for Segmentation of Brain Tumor Images. Sensors 2022, 22, 6501.

10. Shafi, A.S.M.; Rahman, M.B.; Anwar, T.; Halder, R.S.; Kays, H.E. Classification of brain tumors and auto-immune disease using ensemble learning. Inform. Med. Unlocked 2021, 24, 100608.

11. Tandel, G.S.; Tiwari, A.; Kakde, O.G. Performance optimisation of deep learning models using majority voting algorithm for brain tumour classification. Comput. Biol. Med. 2021, 135, 104564.

12. Komaki, K.; Sano, N.; Tangoku, A. Problems in histological grading of malignancy and its clinical significance in patients with operable breast cancer. Breast Cancer 2006, 13, 249–253.

13. Kaplan, K.; Kaya, Y.; Kuncan, M.; Ertunc, H.M. Brain tumor classification using modified local binary patterns (LBP) feature extraction methods. Med. Hypotheses 2020, 139, 109696.

14. Chatterjee, I. Artificial intelligence and patentability: Review and discussions. Int. J. Mod. Res. 2021, 1, 15–21.

15. Raut, G.; Raut, A.; Bhagade, J.; Bhagade, J.; Gavhane, S. Deep learning approach for brain tumor detection and segmentation. In Proceedings of the 2020 International Conference on Convergence to Digital World—Quo Vadis (ICCDW), Mumbai, India, 18–20 February 2020; pp. 1–5.

16. Mamun, M.; Bin Shawkat, S.; Ahammed, M.S.; Uddin, M.M.; Mahmud, M.I.; Islam, A.M. Deep Learning Based Model for Alzheimer's Disease Detection Using Brain MRI Images. In Proceedings of the 2022 IEEE 13th Annual Ubiquitous Computing, Electronics, and Mobile Communication Conference (UEMCON), New York, NY, USA, 26–29 October 2022; pp. 510–516.

17. Tiwari, A.; Srivastava, S.; Pant, M. Brain tumor segmentation and classification from magnetic resonance images: Review of selected methods from 2014 to 2019. Pattern Recognit. Lett. 2020, 131, 244–260.

18. Tandel, G.S.; Biswas, M.; Kakde, O.G.; Tiwari, A.; Suri, H.S.; Turk, M.; Laird, J.R.; Asare, C.K.; Ankrah, A.A.; Khanna, N.N.; et al. A review on a deep learning perspective in brain cancer classification. Cancers 2019, 11, 111.

19. Hollon, T.C.; Pandian, B.; Adapa, A.R.; Urias, E.; Save, A.V.; Khalsa, S.S.S.; Eichberg, D.G.; D'Amico, R.S.; Farooq, Z.U.; Lewis, S.; et al. Near real-time intraoperative brain tumor diagnosis using stimulated Raman histology and deep neural networks. Nature Med. 2020, 26, 52–58.

20. Saeed, F.; Paul, A.; Karthigaikumar, P.; Nayyar, A. Convolutional neural network based early fire detection. Multimedia Tools Appl. 2020, 79, 9083–9099.

21. Saeed, F.; Paul, A.; Hong, W.H.; Seo, H. Machine learning based approach for multimedia surveillance during fire emergencies. Multimedia Tools Appl. 2020, 79, 16201–16217.

22. Simonyan, K.; Zisserman, A. Very deep convolutional networks for large-scale image recognition. arXiv 2014, arXiv:1409.1556.

23. Szegedy, C.; Liu, W.; Jia, Y.; Sermanet, P.; Reed, S.; Anguelov, D.; Erhan, D.; Vanhoucke, V.; Rabinovich, A. Going deeper with convolutions. In Proceedings of the 2015 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Boston, MA, USA, 7–12 June 2015; pp. 1–9.

24. Abd-Ellah, M.K.; Awad, A.I.; Khalaf, A.A.M.; Hamed, H.F.A. Two-phase multi-model automatic brain tumour diagnosis system from magnetic resonance images using convolutional neural networks. EURASIP J. Image Video Process. 2018, 2018, 97.

25. Mercaldo, F.; Brunese, L.; Martinelli, F.; Santone, A.; Cesarelli, M. Object Detection for Brain Cancer Detection and Localization. Appl. Sci. 2023, 13, 9158. https://doi.org/10.3390/app13169158

26. Noreen, N.; Palaniappan, S.; Qayyum, A.; Ahmad, I.; Imran, M.; Shoaib, M. A deep learning model based on concatenation approach for the diagnosis of brain tumor. IEEE Access 2020, 8, 55135–55144.

27. Hossain T, Shishir FS, Ashraf M, Al Nasim MA, Shah FM. Brain tumor detection using convolutional neural network. In2019 1st international conference on advances in Science, engineering and robotics technology (ICASERT) 2019 May 3 (pp. 1-6). IEEE.

28. Mercaldo F, Brunese L, Martinelli F, Santone A, Cesarelli M. Explainable Convolutional Neural Networks for Brain Cancer Detection and Localisation. Sensors. 2023 Sep 2;23(17):7614.

29. Abdusalomov AB, Mukhiddinov M, Whangbo TK. Brain Tumor Detection Based on Deep Learning Approaches and Magnetic Resonance Imaging. Cancers. 2023 Aug 18;15(16):4172.

30. .Khan MA, Khan A, Alhaisoni M, Alqahtani A, Alsubai S, Alharbi M, Malik NA, Damaševičius R. Multimodal brain tumor detection and classification using deep saliency map and improved dragonfly optimization algorithm. International Journal of Imaging Systems and Technology. 2023 Mar;33(2):572-87.

31. Qin C, Li B, Han B. Fast brain tumor detection using adaptive stochastic gradient descent on shared-memory parallel environment. Engineering Applications of Artificial Intelligence. 2023 Apr 1;120:105816.

32. Hossain S, Chakrabarty A, Gadekallu TR, Alazab M, Piran MJ. Vision transformers, ensemble model, and transfer learning leveraging explainable ai for brain tumor detection and classification. IEEE Journal of Biomedical and Health Informatics. 2023 Apr 12.

33. Mahjoubi MA, Hamida S, El Gannour O, Cherradi B, El Abbassi A, Raihani A. Improved Multiclass Brain Tumor Detection using Convolutional Neural Networks and Magnetic Resonance Imaging. International Journal of Advanced Computer Science and Applications. 2023;14(3).

34. Ramtekkar PK, Pandey A, Pawar MK. Innovative brain tumor detection using optimized deep learning techniques. International Journal of System Assurance Engineering and Management. 2023 Feb;14(1):459-73.

35. Saeedi S, Rezayi S, Keshavarz H, R Niakan Kalhori S. MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques. BMC Medical Informatics and Decision Making. 2023 Dec;23(1):1-7.

36. https://labelbox.com/, accessed on 8 August 2023), i.e.

37. Gupta, S., Kumar, P. & Tekchandani, R.K. Facial emotion recognition based real-time learner engagement detection system in online learning context using deep

learning models. Multimed Tools Appl (2022). https://doi.org/10.1007/s11042-022-13558-9

38. Zhang K, Zhang Z, Li Z, Qiao Y (2016) Joint face detection and alignment using multitask cascaded convolutional networks. IEEE Signal Process Lett 23(10):1499–1503

39. Rumelhart, David E., Geoffrey E. Hinton, and Ronald J. Williams. "Learning representations by back-propagating errors." nature 323.6088 (1986): 533-536.

40. Pons, Gerard, and David Masip. "Multi-task, multi-label and multi-domain learning with residual convolutional networks for emotion recognition." arXiv preprint arXiv:1802.06664 (2018).

41. Ding, Dandan, et al. "A CNN-based in-loop filtering approach for AV1 video codec." 2019 Picture Coding Symposium (PCS). IEEE, 2019.

42. Kora, Padmavathi, et al. "Transfer learning techniques for medical image analysis: A review." *Biocybernetics and Biomedical Engineering* 42.1 (2022): 79-107.

43. Ikechukwu, A. Victor, et al. "ResNet-50 vs VGG-19 vs training from scratch: A comparative analysis of the segmentation and classification of Pneumonia from chest X-ray images." *Global Transitions Proceedings* 2.2 (2021): 375-381.

43. Brunese, L.; Mercaldo, F.; Reginelli, A.; Santone, A. An ensemble learning approach for brain cancer detection exploiting radiomic

features. Comput. Methods Programs Biomed. 2020, 185, 105134.

44. https://github.com/ruhyadi/yolo3d-lightning, accessed on 8 August 2023