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requirements of the course Innovative Product
Development under

T. Y. B. Tech. Artificial Intelligence and Machine Learning

By

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University of Mumbai
2023-2024

CERTIFICATE

This is to certify that the project entitled **"OMAD – Brain Tumour Detection"** is a bonafide work of **Abhay Mathur (60017210016)** submitted to the **Department of Artificial Intelligence and Machine Learning** in partial fulfillment of the requirement for the course of Innovative Product Development.

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This is to certify that the project entitled **"OMAD – Brain Tumour Detection"** is a bonafide work of **Mahir Madhani (60017210019)** submitted to the **Department of Artificial Intelligence and Machine Learning** in partial fulfillment of the requirement for the course of Innovative Product Development.

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This is to certify that the project entitled **“OMAD – Brain Tumour Detection”** is a bonafide work of **Darsh Thakkar (60017210040)** submitted to the **Department of Artificial Intelligence and Machine Learning** in partial fulfillment of the requirement for the course of Innovative Product Development.

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This is to certify that the project entitled **“OMAD – Brain Tumour Detection”** is a bonafide work of **Omar Shaikh (60017210088)** submitted to the **Department of Artificial Intelligence and Machine Learning** in partial fulfillment of the requirement for the course of Innovative Product Development.

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Project Report Approval for Innovative Product Development.

This project report entitled ***OMAD – Brain Tumour Detection*** by ***Abhay Mathur (60017210016), Mahir Madhani (60017210019), Darsh Thakkar (60017210040) and Omar Shaikh (60017210088)*** is approved for the course of Innovative Product Development**.**

Examiners

1. ____________________________

2.____________________________

Date:

Place: Mumbai

Declaration

I/We declare that this written submission represents my/our ideas in my/our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

Abhay Mathur (60017210016)

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Abstract

Artificial Intelligence (AI) has emerged as a promising avenue for healthcare advancements. Its implementation in image recognition goes beyond the limitations of human vision, proving especially beneficial in medical imaging for automated diagnosis. Diagnostic radiology is being transformed from a subjective skill into an objective science, thanks to the integration of AI.

Brain tumours have become dangerously common in this day and age. In the U.S., approximately 30 out of every 100,000 adults grapple with brain and nervous system tumors. These growths are worrisome because they can exert pressure on vital brain regions or metastasize. Some may evolve into cancerous forms. They pose a threat by impeding the natural flow of fluid in the brain, which in turn raises pressure within the skull. Moreover, certain varieties have the ability to migrate through spinal fluid, reaching distant parts of the brain or the spinal cord. It's a complex and serious issue that demands attention.

Having researched in the application of Artificial Intelligence and Machine learning in the field of Medicine, our team has decided to work on methods to assist doctors and medical professionals in the early and accurate detection of brain tumours using Machine Learning algorithms.

Table of Contents

List of Figures

List of Abbreviations

Sr. No.	Abbreviation	Expanded form

1. Introduction

AI has incredible potential to transform healthcare, especially in image recognition for medical diagnosis. With AI, we're seeing a shift from subjective interpretations to more objective and scientifically driven analysis, particularly in diagnostic radiology. In the realm of brain tumor detection, AI and Machine Learning (ML) are revolutionizing our approach to this critical medical challenge.

By leveraging advanced Deep Learning algorithms and cutting-edge image recognition and segmentation techniques, AI extends beyond human visual capabilities to aid in the automatic diagnosis of brain tumors from medical images, such as MRI scans. Timely and accurate detection of brain tumors is paramount, given their potential life-threatening nature and the neurological symptoms they can induce by exerting pressure on vital brain structures.

In the United States, brain and nervous system tumors impact about 30 adults per 100,000, underscoring the significance of this issue. Tumors can evolve into malignant and cancerous forms, increasing pressure inside the skull and posing severe risks to brain function and overall health.

Recognizing the urgency of this problem, our aim is to enhance the accuracy of existing Brain Tumor Detection models by exploring larger datasets and state-of-the-art image segmentation models alongside deep learning algorithms. Additionally, we're focused on identifying early symptoms of brain tumors through Machine Learning techniques.

Our objective is to develop a robust machine learning model trained on extensive datasets validated by medical experts. This model aims to produce precise results in detecting brain tumors at the earliest signs of manifestation. We envision this tool as a valuable resource for medical professionals, facilitating immediate and accurate diagnosis, ultimately improving patient care and outcomes

2. Need of the Project

2.1. Why is the project needed?

The urgency of this project stems from the critical need for early detection and precise diagnosis in effectively managing brain tumors. These tumors pose significant challenges in medical practice, especially because their early symptoms are subtle and nonspecific, often leading to delays in diagnosis and treatment initiation. As a result, patients may experience disease progression and increased prognostic risks.

Traditional diagnostic methods, such as manual interpretation of MRI/CT scans, are time-consuming, subjective, and prone to human error. To address these challenges, this project focuses on leveraging state-of-the-art Machine Learning models for semantic segmentation and object detection. These advanced models can automate and accelerate the detection and segmentation process, enabling healthcare professionals to identify tumor regions with greater precision and efficiency.

Moreover, by training these models with meticulously curated extensive datasets, we ensure their robust performance in real-world clinical settings. Additionally, the project delves into automated methods for early symptom detection, which is crucial for improving patient outcomes and quality of life. Early detection of brain tumors is essential for timely intervention and optimal treatment planning.

By developing algorithms capable of identifying subtle indicators of tumor presence within MRI/CT scan images, this project aims to facilitate earlier diagnosis and intervention, thereby enhancing patient care. Ultimately, through the application of cutting-edge Machine Learning techniques and comprehensive research efforts, this project seeks to advance the field of medical imaging and significantly improve patient outcomes in brain tumor management.

2.2. Drawbacks of Existing System

The current methods for detecting and diagnosing brain tumors fall short, highlighting the urgent need for innovation and advancement in this field. Traditional approaches, which rely on manual interpretation of MRI/CT scans, come with several drawbacks. Firstly, they're time-consuming, demanding significant human effort and expertise for accurate analysis. This can cause delays in diagnosis and treatment initiation, potentially impacting patient outcomes negatively. Moreover, manual interpretation is subjective and can vary between individual radiologists, leading to inconsistencies in diagnoses and treatment plans. Additionally, existing systems often struggle to handle the complexity and variability of brain tumor morphology. Tumors come in various shapes, sizes, and locations, making their accurate segmentation and classification a challenge for conventional algorithms. As a result, these systems may struggle to precisely outline tumor boundaries or distinguish between different tumor types, limiting their usefulness in clinical practice. Moreover, many current approaches are trained on outdated or insufficient datasets, further exacerbating their limitations. These datasets may be limited in size or not representative of the diverse range of brain tumors encountered in real-world scenarios. Consequently, the performance of these systems can suffer when applied to new patient populations or unfamiliar tumor types, leading to reduced diagnostic accuracy and reliability.

3. Literature Survey

A literature survey, also known as a literature review, is a comprehensive examination and evaluation of existing academic, scholarly, and relevant sources on a specific topic or research question. It involves systematically reviewing and summarizing the current state of knowledge, theories, and research findings related to the chosen subject. The primary objectives of a literature survey are to gain a deep understanding of existing research, identify gaps in the current knowledge, and establish a theoretical framework for a new study or research project. Researchers conducting a literature survey explore various sources such as books, academic journals, conference papers, and other scholarly publications to provide a well-rounded overview of the existing literature in their field of interest. The findings of a literature survey are crucial for informing the direction of new research and ensuring that it contributes meaningfully to the existing body of knowledge.

[1] Artificial Intelligence Approach for Early Detection of Brain Tumours Using MRI Images by Adham Aleid , Khalid Alhussaini, Reem Alanazi, Meaad Altwaimi, Omar Altwijri and Ali S. Saad

This research introduces a classical automated segmentation approach designed to detect early-stage brain tumours in MRI images. The method relies on a multilevel thresholding technique implemented through a harmony search algorithm (HSO), specially tailored for MRI brain segmentation. The parameters were optimized to suit this particular purpose. By employing multiple thresholds based on variance and entropy functions, the histogram is partitioned into distinct segments, each associated with different colours. Subsequently, morphological operations are applied to remove small areas that could be considered noise, and a connected component analysis is utilized to identify and detect brain tumours after the segmentation process.

The assessment of brain tumour detection performance relies on various performance parameters, including Accuracy, Dice Coefficient, and Jaccard index. These results are then compared to manual assessments conducted by domain experts. Additionally, a comparison is made with different CNN and DLA approaches using the "BraTS 2017 challenge" Brain Images dataset. For this comparison, the average Dice Index serves as the performance measure. The outcomes of the proposed approach exhibit competitive accuracy levels similar to those achieved by CNN and DLA methods. However, the proposed method outperforms these approaches significantly in terms of execution time, computational complexity, and data management.

Future prospects entail investigating and incorporating pixel-based methods within the region of interest to refine the segmentation process. The primary objective is to enhance the accuracy and Dice index of brain tumour detection, leading to more precise diagnoses.

[2] Accurate brain tumour detection using deep convolutional neural network by Md. Saikat Islam Khan, Anichur Rahman, Tanoy Debnath, Md. Razaul Karim, Mostofa Kamal Nasir, Shahab S. Band, Amir Mosavi and Iman Dehzangig

This research introduces two deep learning models for identifying brain abnormalities as well as classifying different tumour grades, including meningioma, glioma, and pituitary. The “proposed 23-layer CNN” architecture is designed to work with a relatively large volume of image data, whereas the “Fine-tuned CNN with VGG16” architecture is designed for a limited amount of image data. A comprehensive data augmentation technique is also conducted to enhance the “Fine-tuned CNN with VGG16” model’s performance.

The experimental results demonstrated that both models enhance the prediction performance of diagnosis of brain tumours. They achieved 97.8% and 100% prediction accuracy for dataset 1 and dataset 2, respectively outperforming previous studies found in the literature.

Future Scope:

In order to make a robust deep learning model, we would require a large dataset i.e. a substantial amount of annotated images collected by a qualified physician or radiologist.

Taking advantage of zero-shot, few-shot, and deep reinforcement learning (DRL) methods could offer promising solutions for addressing this challenge in the future. Zero-shot learning enables the development of recognition models capable of identifying unseen test samples, even without specific training labels. This approach could be particularly beneficial for dealing with the scarcity of training data for different tumor classes. Furthermore, few-shot learning techniques empower deep learning models to extract insights from a limited number of labeled instances per class. Meanwhile, DRL offers a pathway to minimizing the necessity for meticulous annotations and high-quality images. Leveraging these diverse techniques holds potential for advancing our understanding and management of brain and nervous system tumors.

Another future direction is to use more layers or other regularization techniques to work with a small image dataset using CNN model.

[3] MRI-based brain tumour detection using convolutional deep learning methods and chosen machine learning techniques by Soheila Saeedi, Sorayya Rezayi, Hamidreza Keshavarz & Sharareh R. Niakan Kalhori

A dataset containing 3264 Magnetic Resonance Imaging (MRI) brain images comprising images of glioma, meningioma, pituitary gland tumours, and healthy brains were used in this study. First, preprocessing and augmentation algorithms were applied to MRI brain images. Next, they developed a new 2D Convolutional Neural Network (CNN) and a convolutional auto-encoder network, both of which were already trained by our assigned hyperparameters. Then 2D CNN includes several convolution layers; all layers in this hierarchical network have a 2*2 kernel function. This network consists of eight convolutional and four pooling layers, and after all convolution layers, batch-normalization layers were applied. The modified auto-encoder network includes a convolutional auto-encoder network and a convolutional network for classification that uses the last output encoder layer of the first part. Furthermore, six machine-learning techniques that were applied to classify brain tumours were also compared in this study.

The training accuracy of the proposed 2D CNN and that of the proposed auto-encoder network were found to be 96.47% and 95.63%, respectively. The average recall values for the 2D CNN and auto-encoder networks were 95% and 94%, respectively. The areas under the ROC curve for both networks were 0.99 or 1. Among applied machine learning methods, Multilayer Perceptron (MLP) (28%) and K-Nearest Neighbors (KNN) (86%) achieved the lowest and highest accuracy rates, respectively. Statistical tests showed a significant difference between the means of the two methods developed in this study and several machine learning methods (p-value < 0.05).

Future Scope:

Given the critical need for swift and precise diagnosis of brain tumors without delays, exploring the development of alternative robust deep neural networks for tumor classification with reduced execution time and enhanced simplicity is imperative. Therefore, future research could focus on implementing both full machine learning and deep learning algorithms as potential enhancements. Moreover, these proposed techniques could extend beyond brain tumor detection and be applied to identify various types of cancers in MRI or Computed Tomography (CT) scans. This approach holds promise for advancing medical imaging technologies and improving patient care outcomes.

[4] Brain tumour detection from MRI images using deep learning techniques by P Gokila Brindha, M Kavinraj, P Manivasakam and P Prasanth

In this paper ANN and CNN is used in the classification of normal and tumour brain. ANN(Artifical Neural Network) works like a human brain nervous system, on this basis a digital computer is connected with large amount of interconnections and networking which makes neural network to train with the use of simple processing units applied on the training set and stores the experiential knowledge. It has different layers of neurons which is connected together. The neural network can acquire the knowledge by [3] using data set applied on learning process. In a neural network, there's typically one input layer and one output layer, but any number of hidden layers in between. During the learning process, each neuron in these layers receives input from the previous layer and adjusts its weights and biases accordingly based on the input features and the activations from the previous layers. This adjustment is crucial for the network to learn and generate the desired output. Throughout training, the model updates these weights and biases, refining its understanding of the data. Activation functions are applied to the input features and the hidden layers to introduce non-linearity, aiding the network in capturing complex patterns and relationships within the data. This iterative process of adjusting weights and biases, combined with activation functions, facilitates learning and enables the neural network to produce accurate predictions or classifications..

The paper explores the utilization of both Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) for analyzing brain tumor MRI datasets. While ANN operates with fully connected layers, CNN employs convolutional operations, which allow for dimensionality reduction while retaining essential information crucial for training. Various processing techniques such as convolution, max-pooling, dropout, flattening, and dense layers are employed in CNN to construct the model. The paper specifically concentrates on devising a custom architecture for both ANN and CNN models. Finally, it evaluates and compares the performance of ANN and CNN when applied to brain tumor MRI datasets, shedding light on the efficacy of each approach in medical image analysis.

When the ANN model is trained on the training data for fifty epochs, it achieves a training accuracy of 97.13% and a validation accuracy of 71.51%. Subsequently, when applied to the testing data, the model attains an accuracy of 80.77%. Extending the training duration to 200 epochs yields a maximum validation accuracy of 94.00% when evaluated on the training dataset. This suggests that the model continues to learn and improve its performance with more training epochs, albeit with diminishing returns beyond a certain point.

CNN is considered as one of the best technique in analyzing the image dataset. The CNN makes the prediction by reducing the size the image without losing the information needed for making predictions. ANN model generated here produces 65.21% of testing accuracy and this can be increased by providing more image data. The same can be done by applying the image augmentation techniques and the analyzing the performance of the ANN and CNN can be done.

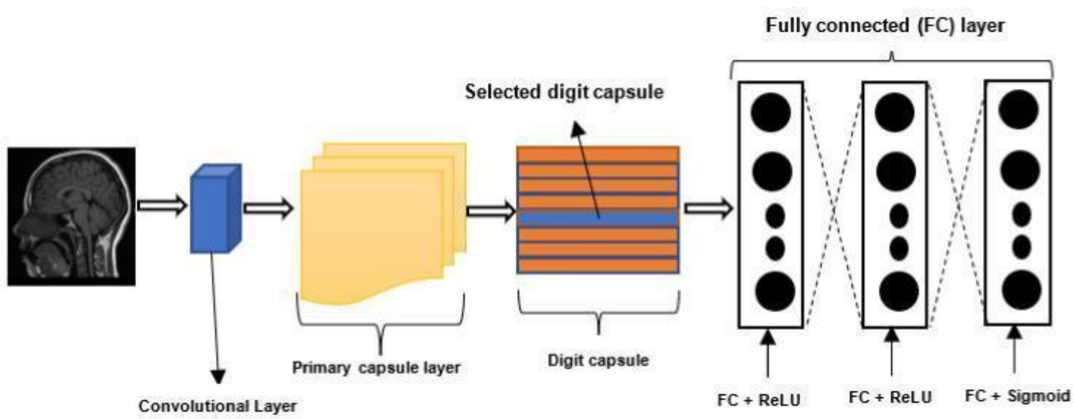
Future Scope:

In future, optimization techniques can be applied so as to decide the number of layers and filters that can used in a model. As of now for the given dataset the CNN proves to be the better technique in predicting the presence of brain tumour.

[5] Brain Tumour Diagnosis Using Machine Learning, Convolutional Neural Networks, Capsule Neural Networks and Vision Transformers, Applied to MRI: A Survey by Andronicus A. Akinyelu, Fulvio Zaccagna, James T. Grist, Mauro Castelli, and Leonardo Rundo

Convolutional Neural Networks (CNNs) represent one of the effective Deep Learning (DL)-based techniques that have been used for brain tumour diagnosis. However, they are unable to handle input modifications effectively. Capsule neural networks (CapsNets) are a novel type of machine learning (ML) architecture that was recently developed to address the drawbacks of CNNs. CapsNets are resistant to rotations and affine translations, which is beneficial when processing medical imaging datasets. Moreover, Vision Transformers (ViT)-based solutions have been very recently proposed to address the issue of long-range dependency in CNNs. This survey provides a comprehensive overview of brain tumour classification and segmentation techniques, with a focus on ML-based, CNN-based, CapsNet-based, and ViT-based techniques.

Despite the remarkable success of CNNs, there are some drawbacks associated with them. First, CNNs require vast datasets for training. Second, CNNs are typically not robust to affine rotations and transformations. Additionally, the routing mechanism employed by CNN's pooling layers is distinct from that employed by the human visual system. The CNN pooling layer routes all the information extracted from the image to all the neurons in the subsequent layer, neglecting essential details or little objects in the image. Capsnet was designed to address the drawbacks of CNN.



Fig, no. 2.5.1 Structure of a CapsNet

A CapsNet is a three-layer network composed of convolutional, primary capsule, and class capsule layers. The primary capsule layer is typically the first one, followed by an undetermined number of capsule layers. The capsule layer is followed by the class capsule layer. The convolutional layer is used to extract features, which are then transmitted to the primary capsule layer. The primary capsule performs a series of operations and transmits the resulting feature map to the digit capsule. Typically, the digit capsule is composed of a n × m weight matrix, where n denotes the number of classes and m the size of each digit capsule. The digit capsule is used to classify the input image before it is fed into the decoder. The decoder consists of three fully connected layers that are used to reconstruct or decode the selected digit capsule into an image.

CapsNet can recognize spatial and hierarchical relationships among objects in images. They are resistant to rotation and image transformations. Additionally, as shown in, CapsNet requires substantially less training data than CNN. Moreover, results reported in the literature show that CapsNet has the potential to improve the accuracy of CNN-based brain tumour diagnosis using a very small number of network parameters.

CNNs have demonstrated state-of-the-art performance in computer vision tasks, such as brain tumour segmentation and classification over the last few years. However, CNNs cannot efficiently capture long-range information or dependencies due to their small kernel size. These long-range dependencies can be effectively handled by techniques that can process sequence relations. A self-attention mechanism in ViTs has the capacity to model long-range dependencies which is very important for precise brain tumour segmentation. They achieve this by modeling pairwise interactions between token embeddings, thus enabling ViT-based models to learn local and global feature representations

Future Scope:

Most of the current research is devoted to brain tumour detection, segmentation, or grade estimation. Most studies did not develop frameworks that can perform these three tasks simultaneously. Moreover, most studies focused on binary-grade classification with less attention paid to multi-grade classification. Designing a framework that can handle brain tumour segmentation, tumour classification (benign versus malignant), and multi-grade estimation would be valuable in improving the decisions and accuracy of medical practitioners when diagnosing brain tumours.

Most of the existing DL brain tumour techniques are based on CNNs. However, these architectures require a huge quantity of data for training. They are also incapable of correctly distinguishing between inputs of different rotations. In addition, obtaining and labelling large-scale datasets is a demanding task [9]. Unfortunately, most publicly available brain cancer datasets are small and imbalanced. The accuracy and generalization performance of a CNN model will be affected if it is trained on small-scale or imbalanced datasets. CapsNet is a recently developed network architecture that has been proposed to address the above-mentioned shortcomings of CNNs. CapsNet are particularly appealing because of their robustness to rotation and affine transformation. CapsNets require significantly less training data than CNN, which is the case for medical imaging datasets such as brain MRI images. CapsNets have the potential to improve the accuracy of CNN-based brain tumour diagnosis using a very small number of network parameters. Most studies did not explore the use of CapsNet for brain cancer diagnosis.

While ViT has demonstrated outstanding performance in NLP, its potential has not been fully explored for medical imaging analysis, such as brain tumour segmentation. Additionally, future research could further investigate the use of Swin transformers, as they seem to perform better than standard ViTs

[6] A Lightweight Deep Learning Based Microwave Brain Image Network Model for Brain Tumour Classification Using Reconstructed Microwave Brain (RMB) Images

The article titled "Enhancing Brain Tumour Classification through a Lightweight Deep Learning Model Utilizing Reconstructed Microwave Brain (RMB) Images" introduces a unique deep learning model designed specifically for categorizing brain tumors using reconstructed microwave brain (RMB) images. This model stands out for its efficiency and low computational requirements, making it suitable for deployment in resource-limited settings. The research team compiled a comprehensive dataset of RMB images featuring various types of brain tumors, using it to train and evaluate the model's performance. The study highlights the impressive accuracy achieved by the proposed model in classifying diverse brain tumors, offering a fresh perspective on tumor classification through RMB images and demonstrating the potential of deep learning in transforming this field.

Similarly, the study titled "Innovative Brain Tumour Segmentation and Classification via Lightweight Deep Learning Models in Sensor-Based Portable Microwave Brain Imaging System" introduces a novel framework tailored for brain tumor segmentation and classification using advanced deep learning techniques. The authors introduce MicrowaveSegNet (MSegNet), a lightweight segmentation model capable of accurately delineating brain tumors, and BrainImageNet (BINet), a classifier proficient in categorizing segmented images into different tumor types. Through rigorous evaluation on a dataset from a sensor-based portable microwave brain imaging system (PMBIS), the study highlights the impressive accuracy of these models in both segmentation and classification tasks. Additionally, the paper discusses the limitations of existing techniques while emphasizing the strengths of the proposed framework, offering a promising approach for advancing brain tumor segmentation and classification using lightweight deep learning models..

[7] SDResU-Net: Separable and Dilated Residual U-Net for MRI Brain Tumour Segmentation by Jianxin Zhang , Xiaogang Lv , Qiule Sun , Qiang Zhang , Xiaopeng Wei and Bin Liu

In this work, the authors propose a novel FCN based network called SDResU-Net for brain tumour segmentation, which simultaneously embeds dilated convolution and separable convolution into residual U-Net architecture.

SDResU-Net introduces dilated block into a residual U-Net architecture, which largely expends the receptive field and gains better local and global feature descriptions capacity.

To fully utilize the channel and region information of MRI brain images, they separate the internal and inter-slice structures of the improved residual U-Net by employing separable convolution operator.

The proposed SDResU-Net captures more pixel-level details and spatial information, which provides a considerable alternative for the automatic and accurate segmentation of brain tumours.

Results and conclusion: The proposed SDResU-Net is extensively evaluated on two public MRI brain image datasets, i.e., BraTS 2017 and BraTS 2018. Compared with its counterparts and stateof- the-arts, SDResU-Net gains superior performance on both datasets, showing its effectiveness.

[8] An early detection and segmentation of Brain Tumour using Deep Neural Network **by** Mukul Aggarwal, Amod Kumar Tiwari, M Partha Sarathi, Anchit Bijalwan

Magnetic resonance image (MRI) brain tumour segmentation is crucial and important in the medical field, which can help in diagnosis and prognosis, overall growth predictions, Tumour density measures, and care plans needed for patients.

The difficulty in segmenting brain Tumours is primarily because of the wide range of structures, shapes, frequency, position, and visual appeal of Tumours, like intensity, contrast, and visual variation. With recent advancements in Deep Neural Networks (DNN) for image classification tasks, intelligent medical image segmentation is an exciting direction for Brain Tumour research.

DNN requires a lot of time & processing capabilities to train because of only some gradient diffusion difficulty and its complication.

To overcome the gradient issue of DNN, this research work provides an efficient method for brain Tumour segmentation based on the Improved Residual Network (ResNet). Existing ResNet can be improved by maintaining the details of all the available connection links or by improving projection shortcuts. These details are fed to later phases, due to which improved ResNet achieves higher precision and can speed up the learning process.

Results: The proposed improved Resnet address all three main components of existing ResNet: the flow of information through the network layers, the residual building block, and the projection shortcut. This approach minimizes computational costs and speeds up the process.

An experimental analysis of the BRATS 2020 MRI sample data reveals that the proposed methodology achieves competitive performance over the traditional methods like CNN and Fully Convolution Neural Network (FCN) in more than 10% improved accuracy, recall, and f-measure.

Outcome of Survey

Most importantly we have understood that we need to find larger datasets validated by medical professionals in with expertise in the field of brain tumours and their early detection. We have also found out that there are some new algorithms and models that have not been explored as much in this field such as CapsNet and Vision Transformers. We intend to find more such models and apply them to the task of brain tumour detection while also attempting to improve accuracy in the models published by previous researchers.

4. Problem Formulation

4.1. Problem Formulation:

This project focuses on the precise detection and segmentation of brain tumors from MRI (Magnetic Resonance Imaging) images, followed by accurate classification into specific tumor types such as Meningioma, Glioma, and Pituitary tumors. Brain tumors present substantial hurdles in medical diagnosis and treatment planning due to their varied characteristics and tendency for rapid advancement. Manual identification and outlining of tumor areas from MRI scans are labor-intensive and susceptible to mistakes. Hence, there's a critical need for automated methods to detect and segment tumors, aiming to enhance the efficiency and precision of diagnosis and treatment..

4.2. Product Objectives:

The product objectives of this project revolve around creating an advanced brain tumor detection and segmentation system utilizing YOLOv8 and TensorFlow CNN models. The primary aim is to develop a robust framework capable of accurately identifying and outlining brain tumor regions from MRI images. This entails implementing YOLOv8 to achieve precise tumor segmentation, ensuring accurate delineation of tumor boundaries. Additionally, the project aims to build a TensorFlow CNN model capable of classifying the segmented tumors into specific types such as Meningioma, Glioma, and Pituitary tumors.

Another key objective is to integrate the segmentation and classification components into a unified system, facilitating seamless analysis and interpretation of MRI data. Furthermore, the project incorporates the use of functional MRI (fMRI) data to enhance the accuracy and reliability of tumor detection and classification, considering the functional aspects of brain regions.

Through these objectives, the project seeks to push the boundaries of medical imaging technology, enhancing its capabilities in diagnosing and treating brain tumors effectively.

4.3. Applications of the Product:

The product's applications span across medical diagnosis, treatment planning, and research, making significant contributions to each domain. In medical diagnosis, it serves as a crucial tool for healthcare professionals, facilitating accurate and efficient detection and diagnosis of brain tumors from MRI images. By automating segmentation and classification processes, the system empowers radiologists and oncologists to pinpoint tumor regions with precision, enabling timely treatment interventions and potentially improving patient outcomes.

In treatment planning, the product provides detailed information on tumor characteristics, including type, size, and location. This data aids in devising personalized treatment strategies tailored to individual patients. Surgeons can utilize segmented tumor regions to plan surgical procedures, ensuring precise tumor resection while minimizing damage to healthy brain tissue. Similarly, radiation oncologists can optimize radiation therapy regimens using tumor classification results, targeting specific tumor types with higher efficacy while minimizing radiation exposure to surrounding healthy tissues.

Moreover, the product serves as a valuable asset in research within the field of brain tumor analysis and medical imaging. Researchers can leverage the system to analyze large datasets of MRI images, studying tumor characteristics and behavior. This includes exploring correlations between tumor features and patient outcomes, investigating novel biomarkers for tumor classification, and evaluating the effectiveness of emerging treatment modalities. Insights gained from such research efforts advance our understanding of brain tumors and drive innovation in diagnostic and therapeutic approaches, ultimately benefiting patient care and outcomes.

4.4. Novelty:

We're delving into a groundbreaking technology known as eMRI, or Epigenetic MRI, to detect DNA methylation in the brain, a crucial factor associated with brain tumor development. This innovation offers the potential for early detection, enabling us to anticipate the likelihood of a brain tumor forming. Through the analysis of DNA changes in brain cells via eMRI scans, our goal is to predict the emergence of brain tumors long before they become physically apparent.

This pioneering approach has the potential to revolutionize our ability to identify potential threats and intervene at an early stage, offering a proactive means of addressing the onset of brain tumors. By detecting DNA methylation patterns indicative of tumor formation, eMRI holds promise in enhancing early diagnosis and ultimately improving patient outcomes in the fight against brain tumors.

4.5. Scope of the Project

The scope of this project involves leveraging cutting-edge Machine Learning models for semantic segmentation and object detection in MRI/CT scan images of brain tumors. By utilizing the latest advancements in the field and exploring unexplored models, the project aims to train these models with professionally validated extensive datasets of such scans.

This includes implementing state-of-the-art techniques to ensure accurate detection and segmentation of brain tumors, thereby enhancing the efficiency and reliability of medical diagnosis. Additionally, the project extends to researching the early symptoms of brain tumors and investigating automated methods for their detection.

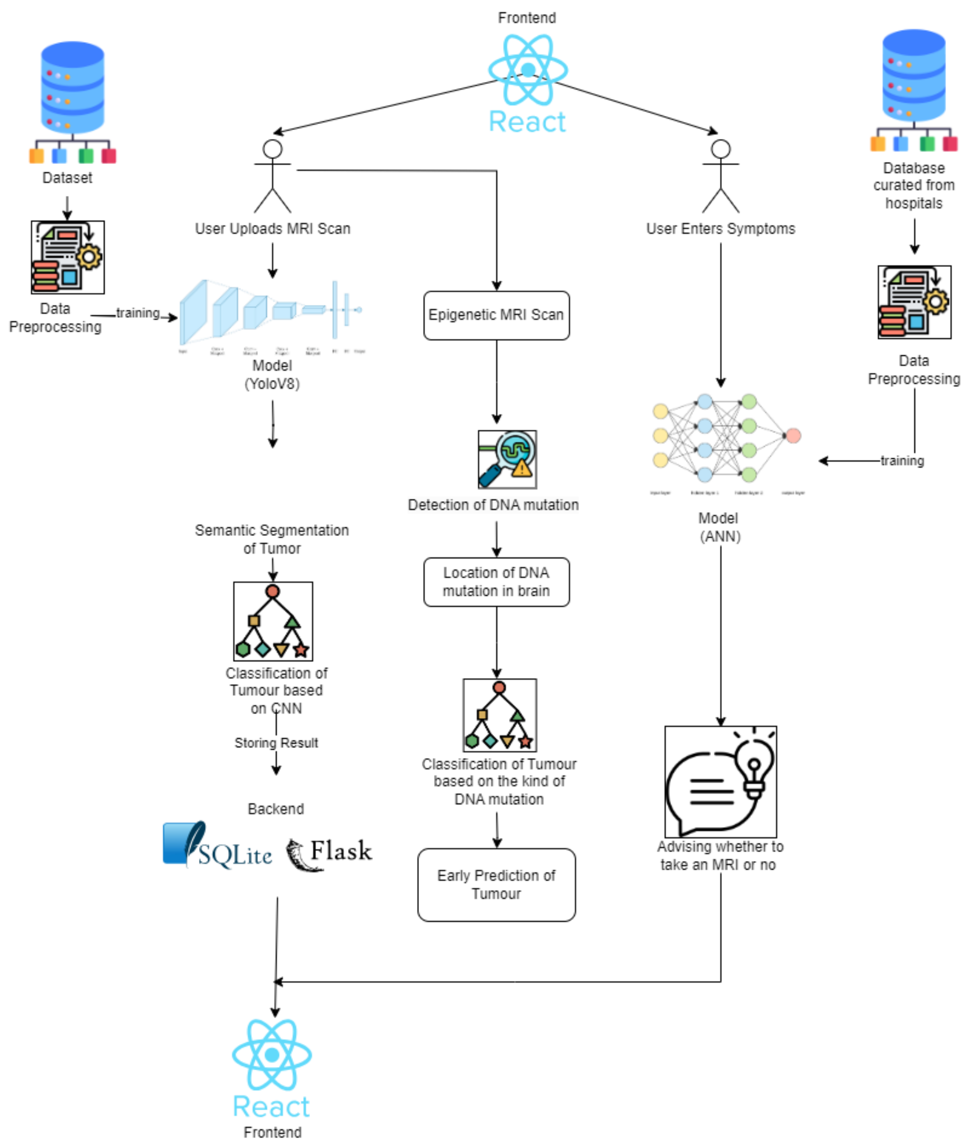
By harnessing machine learning algorithms and extensive datasets, the research aims to identify patterns and indicators associated with early-stage brain tumors, facilitating the development of automated detection systems. Through these efforts, the project aims to contribute to the advancement of medical imaging technology and improve the early diagnosis and treatment of brain tumors.

5. Proposed Design

"OMAD – Brain Tumour Detection" focuses on utilizing machine learning and deep learning models to enhance the accuracy of brain tumor detection in MRI/CT scan images. The project also endeavors to identify and detect potential symptoms of brain tumors at an early stage.

The scope of the project encompasses the utilization of cutting-edge, yet unexplored machine learning models for semantic segmentation and object detection in MRI/CT scan images of brain tumors. This involves training these models with meticulously validated expansive datasets of such scans.

Moreover, the project includes conducting research on the early symptoms of brain tumors and exploring methods to automate their detection. Through these efforts, "OMAD – Brain Tumour Detection" aims to advance the field of medical imaging and contribute to the early diagnosis and treatment of brain tumors.



5.1 Mathematical Approach

The mathematical approach underlying the brain tumor detection, segmentation, and classification application involves several key equations and operations.

Firstly, in the YOLOv8 object detection phase, the model predicts bounding box coordinates and class probabilities for each detected object. The bounding box coordinates are calculated using sigmoid and exponential functions, as follows:

$$b_x = \sigma(t_x) + c_x$$

$$b_y = \sigma(t_y) + c_y$$

$$b_w = p_w \cdot e^{t_w}$$

$$b_h = p_h \cdot e^{t_h}$$

Where b_x,b_y represent the center coordinates of the bounding box, b_w , b_h represent its width and height, and c_x ,c_y ,p_w ,p_h are predefined parameters. The class probability prediction is given by:

$$P(Class_i|Object) = \sigma(t_o) \cdot P(Class_i)$$

Where □ is the sigmoid activation function. Additionally, the Intersection over Union (IoU) metric is used to evaluate the overlap between predicted and ground-truth bounding boxes:

$$IoU = \frac{Area(Overlap)}{Area(Union)}$$

Next, in the convolutional neural network (CNN) for classification, various mathematical operations are applied. The convolution operation computes feature maps by convolving input data with learnable filters. The Rectified Linear Unit (ReLU) activation function introduces non-linearity by thresholding negative values to zero:

$$ReLU(x) = \max(0, x)$$

Pooling operations, such as max pooling, downsample feature maps to reduce dimensionality:

$$\text{MaxPool}(x, y) = \max(x, y)$$

In the fully connected layer, the output is computed using a linear transformation followed by an activation function:

$$y = Wx + b$$

Lastly, the Softmax activation function normalizes the output of the network into a probability distribution over multiple classes:

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

In terms of optimization, techniques like stochastic gradient descent (SGD) and the Adam optimizer are commonly used. SGD updates model parameters based on the gradient of the loss function with respect to those parameters:

$$\theta_{t+1} = \theta_t - \eta \nabla J(\theta_t)$$

Where \(\eta\) is the learning rate and \(J(\theta_t)\) is the loss function. The cross-entropy loss function measures the difference between predicted and actual class probabilities:

$$\text{CE Loss} = -\sum_i y_i \log(\hat{y}_i)$$

Adam optimization adapts the learning rate for each parameter based on the first and second moments of the gradients:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$$

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t}$$

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t} + \epsilon} \hat{m}_t$$

These equations form the basis of the mathematical framework used to detect, segment, and classify brain tumors in medical images. They facilitate the effective processing and interpretation of MRI scans, aiding in the diagnosis and treatment of patients.

5.2 ML-Based Model Approach

Users engage with the application through a user-friendly React frontend interface, where they can input personal details and upload MRI scan images for tumor detection and classification. Once submitted, the data and images are sent to a Flask backend server for processing. Acting as the bridge between the frontend and machine learning models, the Flask backend manages the entire workflow seamlessly.

The uploaded MRI scan images undergo segmentation using a YOLOv8-based model. This segmentation model identifies and highlights tumor regions within the images. If a tumor mask is predicted, indicating tumor presence, the segmented image proceeds to the next stage.

Next, the segmented tumor images are analyzed by a classification model implemented using TensorFlow and Keras. This Convolutional Neural Network (CNN) is trained to categorize tumors into meningioma, glioma, or pituitary types. By examining features from the segmented tumor images, the CNN predicts the most probable tumor type.

After classification, the Flask backend sends the segmented and classified MRI scan images back to the React frontend. The response includes the segmented image along with the predicted tumor type, allowing users to visualize the segmentation and classification outcomes effectively.

In the React frontend, the segmented and classified MRI scan images are presented in a tabular format alongside the user's details. Users can interact with these images, such as clicking to enlarge or view more detailed information. This frontend offers a seamless user experience, aiding medical diagnosis and decision-making by presenting the predicted tumor type alongside the corresponding MRI scan image.

5.3 Use Cases

The brain tumor detection, segmentation, and classification application emerge as a versatile tool with wide-ranging applications in healthcare. Primarily, it acts as a crucial aid in medical diagnosis and treatment planning. Through precise detection, segmentation, and classification of tumors from MRI scans, healthcare professionals can make informed decisions about patient care, selecting the most suitable treatment options like surgery, radiation therapy, or chemotherapy. This capability enhances diagnostic accuracy and efficiency, ultimately leading to better patient outcomes and quality of care.

Moreover, the application facilitates research and clinical studies by providing a streamlined platform for analyzing extensive datasets of MRI scans. Researchers and clinicians can leverage its automated functionalities to study brain tumor characteristics and behavior, advancing our understanding of tumor biology and aiding in the development of more effective treatment strategies.

Beyond diagnostic and research purposes, the application supports telemedicine and remote consultations, addressing the challenge of accessing specialized medical expertise in remote or underserved areas. Through telemedicine, patients can receive timely assessments and recommendations based on their MRI scans, overcoming geographical barriers and enhancing healthcare accessibility. Additionally, the application serves as an educational resource for medical students, residents, and healthcare professionals, offering hands-on learning experiences in brain tumor diagnosis and management.

As a clinical decision support system, the application complements the expertise of radiologists and healthcare providers by providing reliable assistance in MRI scan interpretation and diagnostic decision-making. By delivering accurate tumor detection, segmentation, and classification outcomes, it streamlines the diagnostic process and facilitates personalized treatment planning for patients.

Finally, the application can be integrated into early detection and screening programs for brain tumors, allowing for routine screening of individuals at risk or with symptoms suggestive of brain tumors. This proactive approach to detection enables the identification of tumors at an early stage, when treatment options may be more effective, thereby improving patient outcomes and survival rates.

6. Implementation

6.1 Mathematical Approach

The YOLOv8 algorithm predicts bounding boxes and class probabilities for objects within MRI scan images. Mathematically, the bounding box prediction can be represented as follows:

$$b_x = \sigma(t_x) + c_x$$

$$b_y = \sigma(t_y) + c_y$$

$$b_w = p_w \cdot e^{t_w}$$

$$b_h = p_h \cdot e^{t_h}$$

where b_x,b_y are the center coordinates of the box, b_w,b_h are the width and height, (c_x,c_y) are the coordinates of the grid cell, (t_x,t_y) are the offsets, (t_w, t---$_h$)are the width and height adjustments, p_w,p_h are anchor box dimensions, and σ denotes the sigmoid function.

Additionally, class probabilities, P(class| object) for different object categories are predicted for each bounding box using a softmax function:

$$P(\text{class}|\text{object}) = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}}$$

where z_i represents the class score for the i-th class, and □ is the total number of classes.

Classification Approach:

The CNN architecture used for tumor classification involves several layers, including convolutional layers, pooling layers, and fully connected layers. Mathematically, the output feature map □□Hi of a convolutional layer can be computed as:

$$H_i = f_i(H_{i-1} * W_i + b_i)$$

where □$_i$ is the activation function, □$_{i-1}$ is the input feature map, W_i is the filter weights, and □$_i$ is the bias term.

Pooling layers downsample the feature maps, typically using max-pooling operations:

$$\text{MaxPool}(x) = \max(x)$$

Fully connected layers integrate the extracted features for classification:

$$Z^{[l]} = W^{[l]} A^{[l-1]} + b^{[l]}$$

where $Z^{[l]}$ is the output of the l-th layer, $W^{[l]}$ and $B^{[l]}$ are the weights and biases, and $A^{[l-1]}$ is the input activation from the previous layer.

The loss function for classification tasks is typically categorical cross-entropy, computed as:

$$L(y, \hat{y}) = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

where y is the true class label, y^ is the predicted class probabilities, and N is the number of classes.

6.2 ML-Based Model Approach

One of our most significant and persistent problems throughout our research phase was the lack of sufficient validated medical data appropriate for our use case. The publicly available free datasets are not enough to train a model with the kind of accuracy that we aspire to achieve in our model. Therefore, we took it upon ourselves to find a solution to this problem, which was to artificially generate large amounts of data to train our model on using a Generative Adversarial Network (GAN) model. We performed horizontal-flip data augmentation on the data we currently had and then passed it to our GAN model to generate a larger dataset of brain tumour MRI scans. We then trained our segmentation and classification models on a combination of the original augmented dataset and the GAN generated dataset to obtain optimal results and better accuracy.

For the segmentation of brain tumors in MRI scans, we employ YOLOv8, an advanced object detection algorithm renowned for its speed and accuracy in identifying objects within images. YOLOv8, short for "You Only Look Once version 8," operates by dividing the input image into a grid and predicting bounding boxes and class probabilities for each grid cell. In our context, the model is trained to detect the presence and location of tumors within the MRI scan. We train the model using labeled MRI images where tumors are annotated with bounding boxes.

During training, YOLOv8 optimizes a loss function that penalizes errors in bounding box coordinates and class predictions. This loss function incorporates components for localization loss, confidence loss, and classification loss. Through iterative optimization using techniques like stochastic gradient descent (SGD) or Adam optimization, the model learns to accurately localize and classify tumors in MRI images.

Once trained, the YOLOv8 model efficiently processes new MRI scans and predicts bounding boxes around detected tumors. These bounding boxes represent the segmented regions of the MRI scan that contain suspected tumors, providing valuable information for further analysis and classification of the tumors.

Following tumor segmentation, the segmented regions from the MRI scans undergo classification using a convolutional neural network (CNN). CNNs are particularly well-suited for image classification tasks due to their ability to automatically learn hierarchical features from input data. In our application, we design and train a custom CNN architecture to classify tumors into specific categories, namely meningioma, glioma, or pituitary tumors.

The CNN architecture comprises several layers, including convolutional layers, pooling layers, and fully connected layers. In the convolutional layers, feature maps are generated by convolving input images with learnable filters, capturing spatial patterns indicative of different tumor types. Pooling layers downsample feature maps to reduce dimensionality and extract key features. Subsequently, fully connected layers integrate extracted features to make predictions about tumor classes.

During training, the CNN model learns to differentiate between tumor classes by minimizing a loss function, such as categorical cross-entropy. The loss function quantifies the disparity between predicted and ground-truth tumor labels, guiding the optimization process. Techniques like gradient descent-based optimization and regularization are employed to fine-tune model parameters and prevent overfitting.

Once trained, the CNN model can classify segmented tumor regions into meningioma, glioma, or pituitary tumors with high accuracy. The classification results provide clinicians with crucial insights into the nature and type of tumors present in MRI scans, facilitating diagnosis and treatment planning for patients.

7. Experimentation & Results

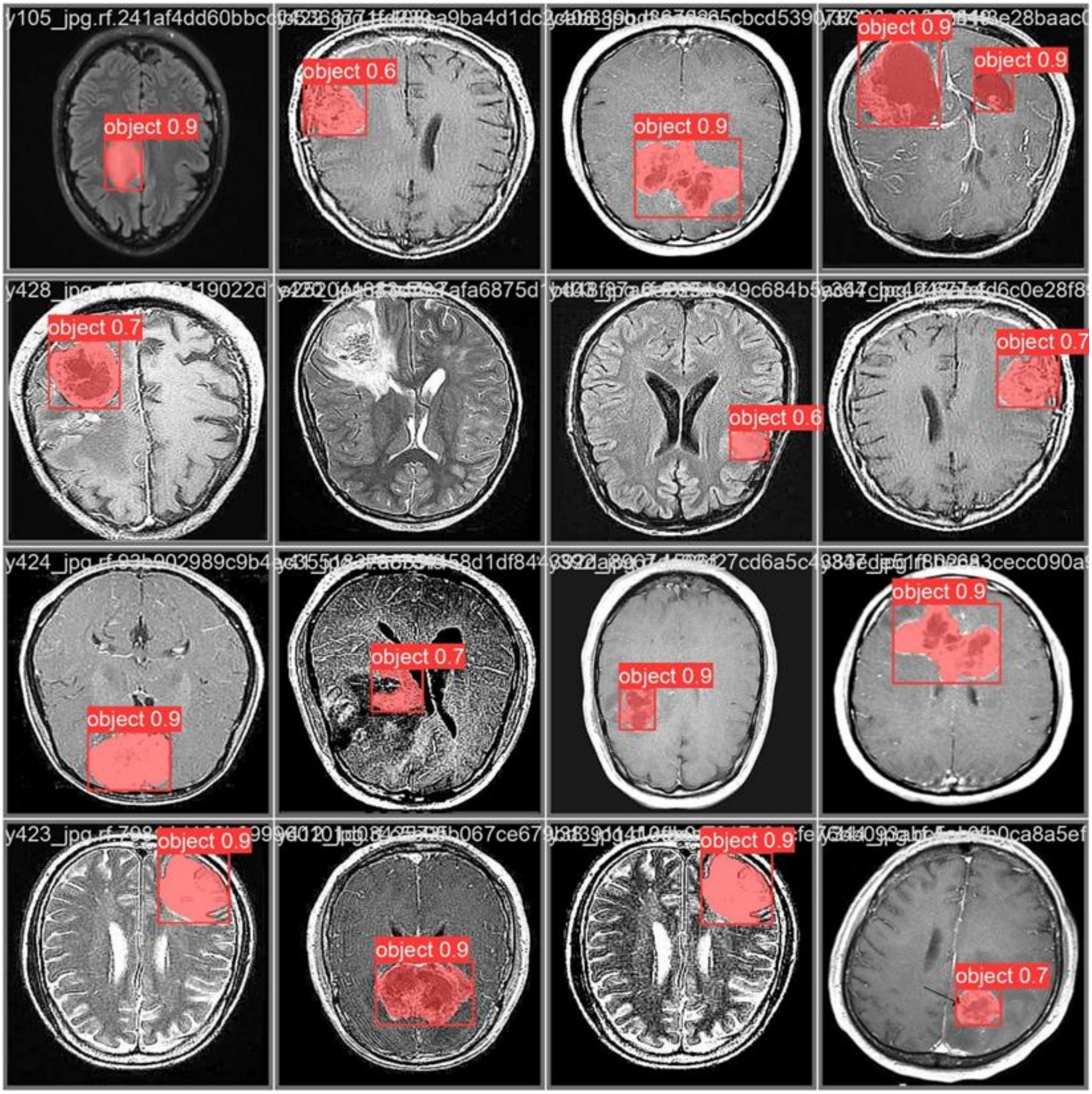
We trained YOLOv8seg, ViT and SAM models on a brain tumour detection dataset ‘celebal-p3kbm’ from Roboflow and got the following results:

YOLOv8seg (CNN):

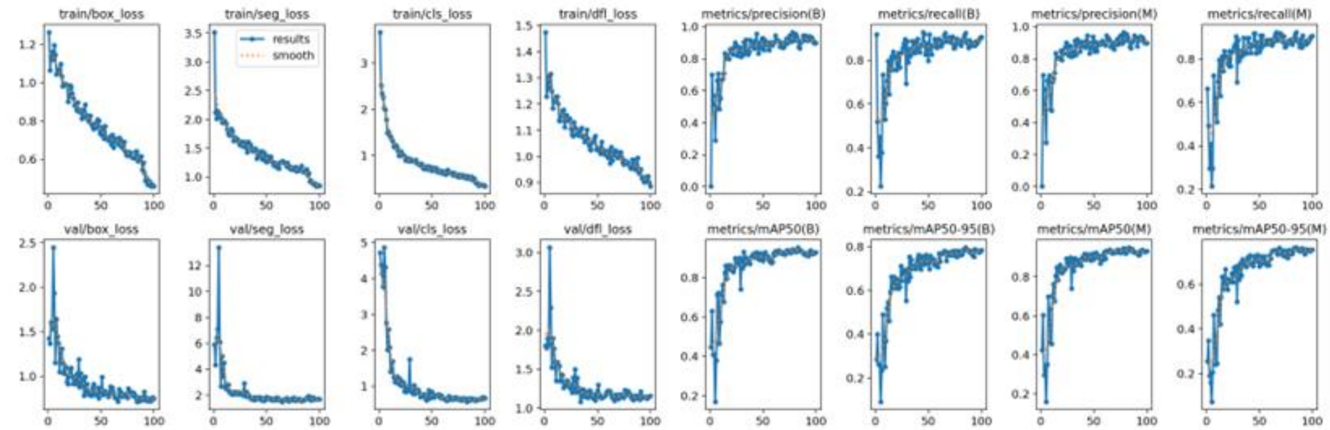
We have achieved 93.5% with a CNN-based YOLOv8 segmentation model so far.

```
YOLOv8n-seg summary (fused): 195 layers, 3258259 parameters, 0 gradients, 12.0 GFLOPs
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95)     Mask(P
                   all        100         98      0.866      0.923      0.935      0.796      0.866
Speed: 0.4ms preprocess, 6.4ms inference, 0.0ms loss, 7.1ms postprocess per image
```

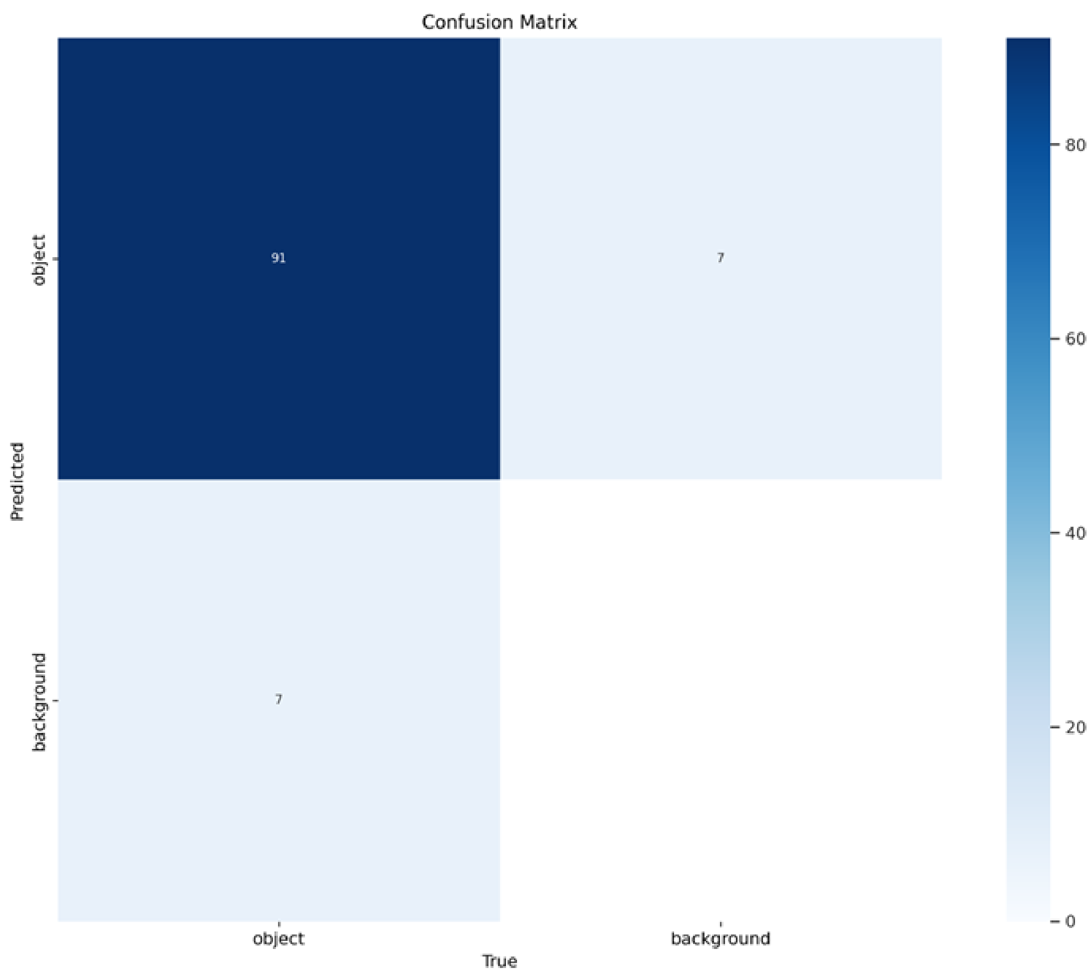
Fig, no. 5.1 Training Results



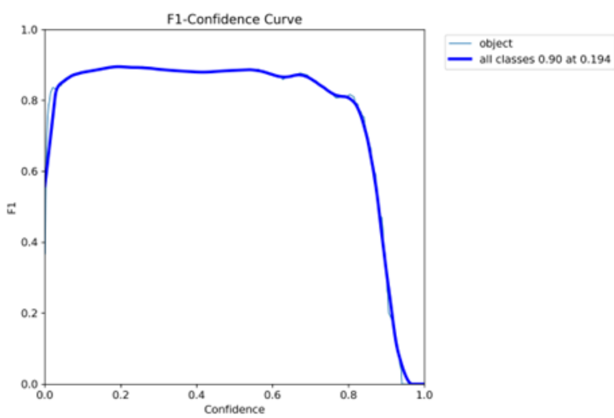
Fig, no. 5.2 Validation Batch

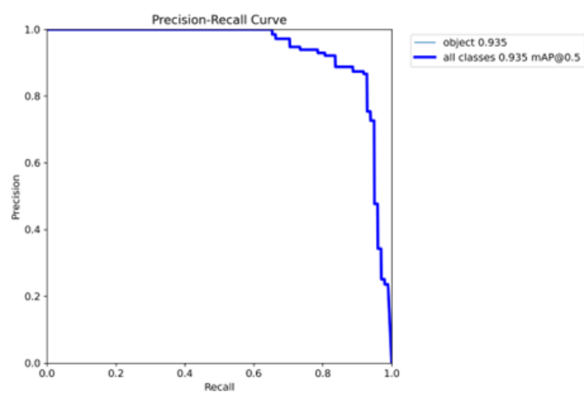


Fig, no. 5.3 Graphs of Training Results

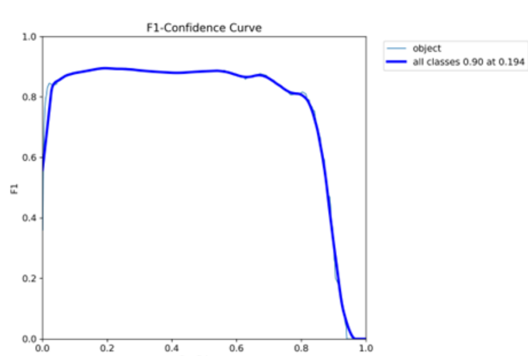


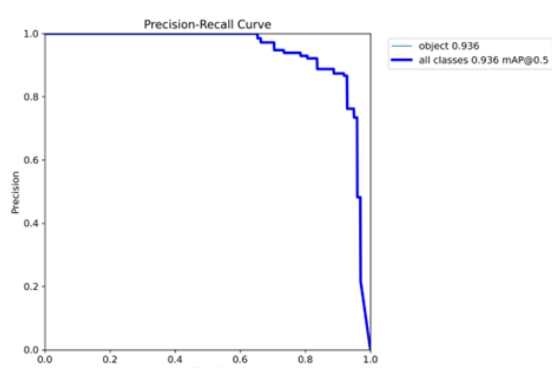
Fig, no. 5.4 Confusion Matrix



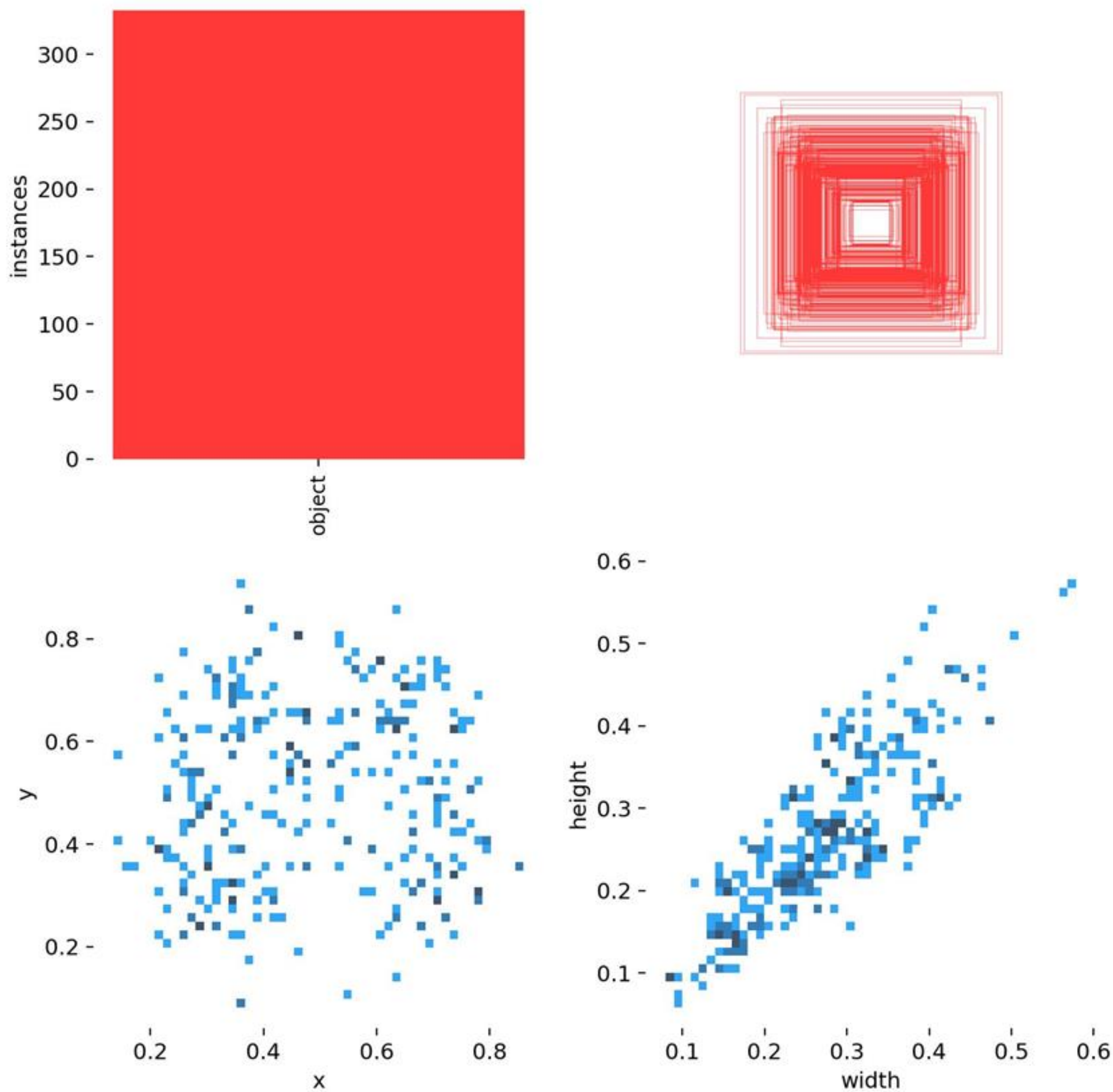


Fig, no. 5.5 Precision and Recall Curves for Box

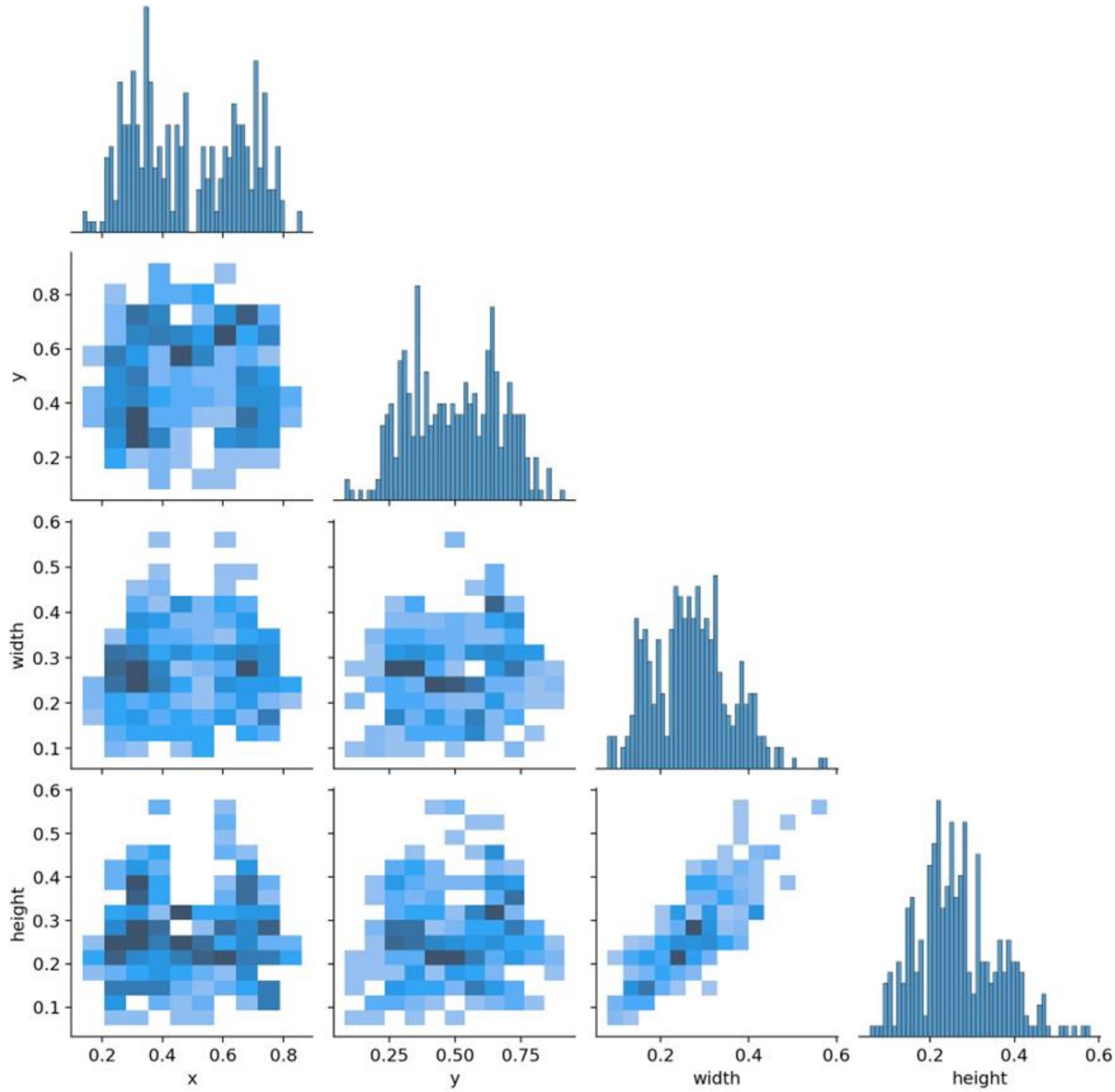




Fig, no. 5.6 Precision and Recall Curves for Mask

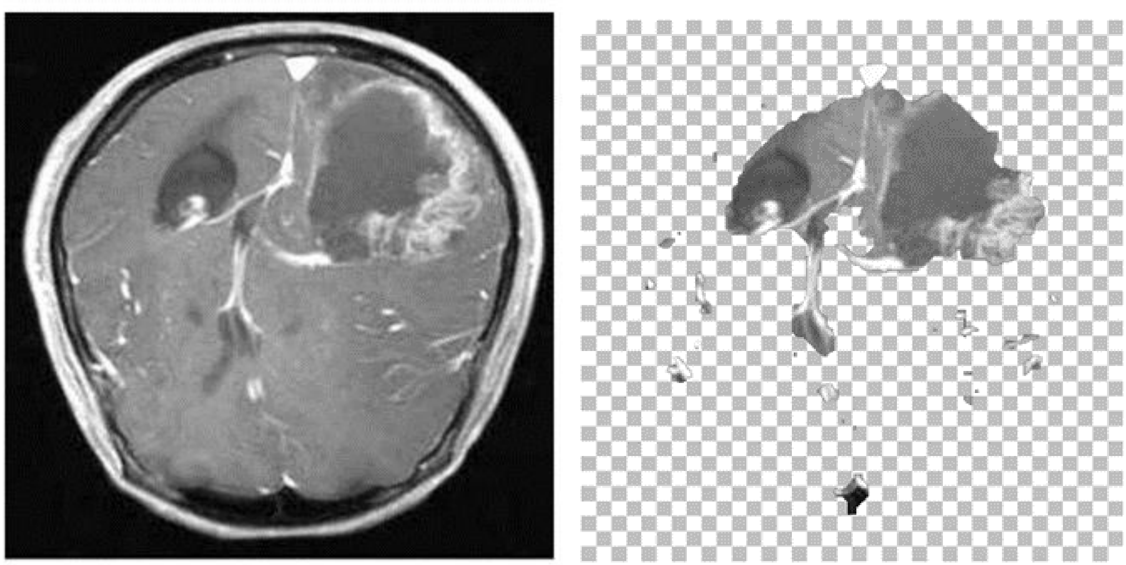


Fig, no. 5.7 Inference from Labels



Fig, no. 5.8 Labels Correlogram

ViT (Vision Transformer):

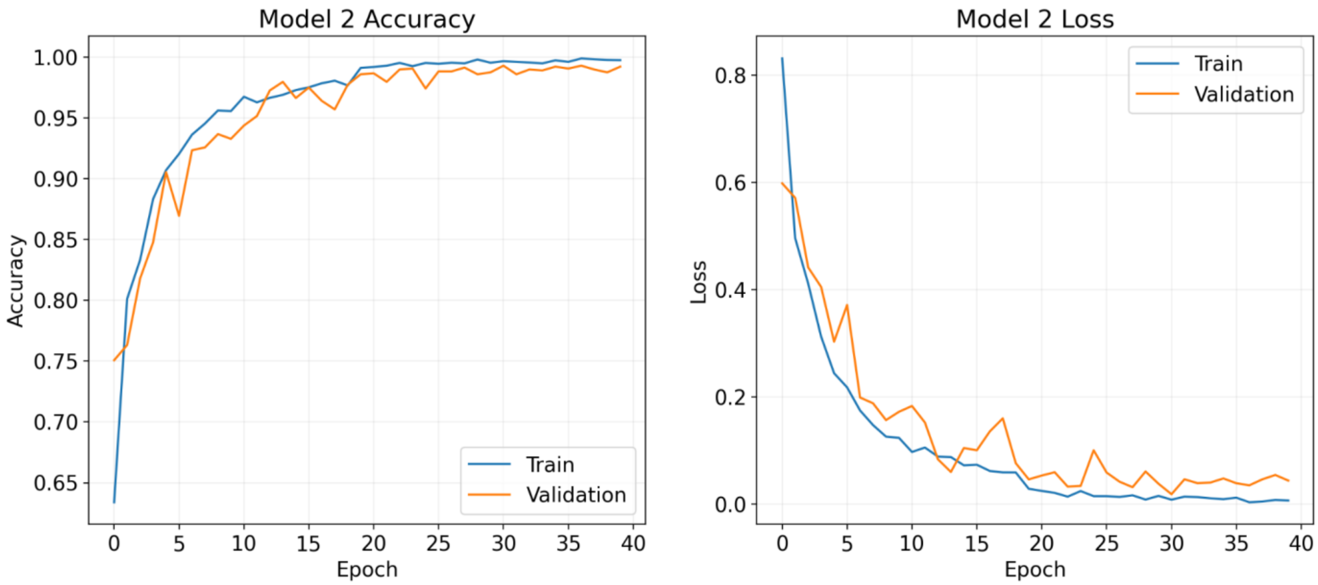


Fig, no. 5.9 ViT Segmentation Results

CNN (For Classification)

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 147, 147, 32)      1568

 max_pooling2d (MaxPooling2  (None, 49, 49, 32)        0
 D)

 conv2d_1 (Conv2D)           (None, 46, 46, 64)        32832

 max_pooling2d_1 (MaxPoolin  (None, 15, 15, 64)        0
 g2D)

 conv2d_2 (Conv2D)           (None, 12, 12, 128)       131200

 max_pooling2d_2 (MaxPoolin  (None, 4, 4, 128)         0
 g2D)

 conv2d_3 (Conv2D)           (None, 1, 1, 128)         262272

 flatten (Flatten)           (None, 128)               0

 dense (Dense)               (None, 512)               66048

 dropout (Dropout)           (None, 512)               0

 dense_1 (Dense)             (None, 4)                 2052

=================================================================
Total params: 495972 (1.89 MB)
Trainable params: 495972 (1.89 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

```
40/40 [==============================] - 5s 121ms/step - loss: 0.0441 - accuracy: 0.9922
Test Loss: 0.04409
Test Accuracy: 0.99219
```



8. Conclusion and Future Scope

Brain Tumours are an ever-increasing medical problem and this field has an immense scope of research work in terms of detection automation.

After conducting thorough research and surveying multiple articles and papers about brain tumour detection we have come to the conclusion that the most optimal way to do this is by trying to implement various cutting edge methods and models of semantic segmentation (for eg: YOLOv8 from ultralytics) and various new and unexplored Deep Learning models based on the base architecture of Convolutional Neural Networks (CNNs) such as CapsNet. ViT, etc.

We can also address detection of early signs of brain tumours by detecting changes in the DNA of brain cells such as DNA methylation which can be a cause of Brain tumours using Epigenetic MRI scans.

The current project marks a significant advancement in brain tumor detection automation, with promising avenues for future development. By integrating state-of-the-art techniques like semantic segmentation and advanced deep learning models such as Capsule Networks (CapsNet) and Vision Transformers (ViT), the system achieves higher accuracy and efficiency in tumor detection. Future enhancements include incorporating additional imaging modalities and data sources like fMRI and DNA methylation patterns for a more comprehensive understanding of tumor biology. Developing a clinical decision support system (CDSS), conducting validation studies, and promoting global accessibility are key objectives to ensure widespread adoption and impact in healthcare.

9. Publication

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1.1 Report Writing

1.1.1 Guidelines for Report Writing

All text should be Times New Roman, 12 font size and Justified. Both side 1-inch margin should be left. Set spacing to 1.5. Every new chapter should be stated from a new page. All the figures should be centered and the labels should be below the figure in 10 Times New Roman. All the tables should be centered and labels should be above the table in 10 Times New Roman. Report should not use I/We. All the references, figures and tables should be cited.

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